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INFERENTIAL RELATIONSHIPS IN THERMOMECHANICAL PULP REFINING, EXPLORED USING MULTIVARIATE ANALYSIS

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INFERENTIAL RELATIONSHIPS IN THERMOMECHANICAL PULP REFINING, EXPLORED USING MULTIVARIATE ANALYSIS

présentée par : HARRISON Robert
en vue de l'obtention du diplôme de : Philosophiae Doctor
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RÉSUMÉ

L'analyse multivariée (AMV) est utilisée couramment dans l'industrie pour diagnostiquer les problèmes, suivre les procédés, et contrôler les systèmes, et elle est devenue facilement accessible via les logiciels commerciaux. Par contre, cette technique statistique aux moindre-carrés demeure très susceptible à la devise « garbage-in/garbage-out », notamment en ce qui concerne les perturbations de procédé et les autres valeurs aberrantes. Les données de production sont souvent assujetties aux valeurs aberrantes, à la dérive des instruments, et aux arrêts et aux départs d'unités d'opérations, et l'échantillonnage des produits est souvent peu fréquent.

La clientèle du secteur des pâtes et papiers, comme celle de bien des industries globalisées, exige de plus en plus un meilleur produit à un prix plus compétitif. L'analyse de la vaste quantité de données sur les procédés et sur les produits qui sont accumulés dans les serveurs informatiques représente une stratégie importante pour atteindre cet objectif. Les procédés papetiers sont, de nature, multivariés, c'est-à-dire que les interactions entre les variables sont tout aussi importantes que les variables elles-mêmes. Pour en extraire le bénéfice maximal, il faut donc modéliser ces variables en groupes.

En prenant comme étude de cas une usine de pâte thermo-mécanique (PTM) dans l'Est du Canada, nous avons comparé plusieurs méthodes de sélection et de prétraitement des données brutes pour maximiser le réalisme et l'utilité des modèles AMV.

Nous avons tiré une conclusion importante : les modèles générés avec la variante de l'AMV connue sous le nom « Partial Least Squares » (PLS) ont été améliorés en prétraitant les données, non seulement par rapport à leur signification statistique, mais également en termes de leur interprétation physique. Nous avons donc recommandé une approche globale pour l'application de l'AMV aux données d'opérations industrielles, incluant une méthode systématique pour enlever les périodes d'opération questionnables comme la production à la baisse ou les comportements aberrants, ainsi que le filtrage de toutes les variables.

Le prochain défi était de développer une méthode pour corréler les opérations PTM à la qualité de la pâte et, ultimement, au papier en mettant l'emphase sur les principes fondamentaux tels l'énergie spécifique et l'intensité de raffinage. L'usine dont il est question subit des variations importantes dans la force et la porosité du papier bien connus pour être affectés par les conditions de raffinage de pâte en amont. Les interruptions fréquentes des lignes de raffinage font varier énormément l'énergie spécifique et d'autres paramètres clés, dont plusieurs ne sont pas mesurés directement et doivent être

calculés à partir des mesures existantes. À cause de la basse fréquence des mesures, établir le lien entre les variations dans les propriétés du papier et les caractéristiques de la pâte tels l'indice d'égouttement, la longueur de fibre, et le contenu en matières fines est difficile. Pourtant, les lignes de raffinage sont riches en termes de données, avec de nombreuses variables qui sont mesurées chaque seconde. Malheureusement, les données de qualité des copeaux de bois étaient extrêmement limitées et peu fréquentes, et ont très peu contribué aux modèles AMV.

Une section importante, et parfois oubliée, de toute usine PTM est le raffinage des rejets. Le taux de production aux presses, ainsi qu'aux raffineurs de rejets, change continuellement parce que l'usine a souvent des arrêts et des départs sur les quatre lignes principales de raffinage. Pour compenser, les opérateurs vont augmenter le taux de rejet quand une ligne est arrêtée, ce qui fait changer la distribution de longueur de fibres de la pâte envoyée aux rejets. Cette situation, en combinaison avec les arrêts occasionnels des raffineurs de rejets eux-mêmes, mène à un raffinage de rejets qui est très variable et moins bien contrôlé.

En utilisant l'AMV et d'autres outils statistiques, il a été possible de relier la qualité du produit aux opérations de PTM et de rejets, en tenant compte du nombre de lignes en opération, de l'âge des plaques, et des délais de procédé. Les meilleurs modèles ont été obtenus sur une échelle de temps plus courte (1 heure), avec un filtrage à moyenne pondérée pour aider à combler l'écart entre les mesures d'opération rapides et les mesures de qualité lentes.

Nous avons développé une méthodologie détaillée et explicite pour l'application de l'AMV aux données de production, à partir des résultats énumérés ci-dessus. Pour résumer, la méthodologie consiste à définir les objectifs de la modélisation, examiner les données de production, créer une structure de modèle basée sur les principes fondamentaux, prétraiter les données, bâtir les modèles, interpréter les résultats statistiques, et finalement identifier les limitations du modèle.

En suivant cette méthodologie, il a été possible d'utiliser l'AMV pour corréler environ la moitié de la variabilité dans la qualité du papier final aux opérations de raffinage. Les variables en amont qui se sont avérées les plus marquantes sont l'âge des plaques, l'énergie spécifique (incluant l'énergie du raffinage des rejets), la consistance de raffinage, le nombre de lignes PTM en opération, et la variabilité de charge des moteurs représentée par l'écart-type. Le cas d'étude a donné des résultats qui étaient non seulement significatifs statistiquement, mais qui étaient également interprétables par rapport aux principes fondamentaux du procédé.

Étant donné qu'aucun modèle n'a pu couvrir tous les scénarios de production, il semblerait qu'un contrôleur adaptatif serait requis pour automatiser le procédé de raffinage PTM. Il est possible à partir d'un modèle PLS de prédire de nouvelles valeurs Y à partir de nouvelles valeurs X. Par contre, il y a une variation énorme entre les coefficients d'un mois à l'autre, en pourcentage de l'ordre de plusieurs centaines. De toute manière, quelque soit le type de contrôle de procédé envisagé, il faudrait tenir compte des délais de procédé, du filtrage, et des moyennes dans le temps pour bien capter la dynamique du procédé.

ABSTRACT

Multivariate Analysis (MVA) is widely used for troubleshooting, monitoring and controlling industrial processes, and has become easily accessible to plant engineers through desktop software packages. However, this least-squares statistical technique remains highly susceptible to the adage "garbage-in/garbage-out". Production data are rife with outliers, instrument drift, starts and stops of key unit operations, and often product quality sampling is relatively infrequent.

The pulp and paper sector, like many globalized industries, finds itself with an increasingly demanding clientele who continually expect a better and cheaper product. An important design strategy for addressing this objective is the analysis of the vast quantity of process and product data accumulated in plant-wide data historians. Mill processes are multivariate, meaning that the interactions between the variables are as important as the variables themselves. To extract the maximum benefit, process relationships must therefore be modelled as a group.

Using a Thermo-Mechanical Pulp (TMP) newsprint mill in Eastern Canada as a case study, we compared various ways of selecting and pre-treating raw process data to maximize the realism and usefulness of the black-box pulp quality models. A major conclusion was that models generated using an MVA variant known as Partial Least Squares (PLS) were significantly improved by pre-treating the data, with respect to both statistical significance and physical interpretability. We recommended an overall approach for applying MVA to industrial operating data, involving a systematic method for removing dubious periods of operation such as low production and aberrant process behavior, and filtering of all variables.

The next challenge was to develop a method for correlating TMP operations with pulp and, ultimately, paper quality by focusing on process fundamentals such as specific energy and refining intensity. The case study mill experiences variability in paper strength and porosity, which are known to be affected by upstream pulp refining conditions. Frequent interruptions in the refining lines greatly affect the specific energy and other key parameters, some of which are not measured directly and must be calculated from other variables. Due to the infrequency of measurements, linking paper variations to upstream pulp quality variables such as freeness, fiber length and fines content is difficult. However, the mainline refining and reject sections are 'data rich', with many parameters measured second-by-second. Unfortunately, data on the incoming wood chips were extremely sparse, and were found to contribute little to the MVA models.

A very important, and sometimes overlooked, part of any TMP mill is reject refining. Because the case study mill experiences frequent starts and stops on the four main refining lines, the throughput at the presses, and ultimately the reject refiners, is continually changing. Partly to compensate for this, the operators increase the reject rate after a line stoppage, which changes the fibre length distribution of the pulp entering the reject refiners. Combined with occasional stoppages of the reject refiners themselves, this situation results in reject refining that is highly variable and less well controlled.

Using Multivariate Analysis and other statistical tools, it was possible to link product quality back to TMP and rejects operations, taking into account number of lines in operation, plate age and process lags. The best MVA models were obtained by using a shorter (1-hour) data timescale, with a weighted-average filter helped to bridge the gap between the faster readings and slower paper quality trends.

Based on the above results, we have developed an explicit, detailed methodology for applying MVA to production data which addresses these challenges. In summary, the methodology involves defining the modelling objectives, examining product data, building a suitable model structure using process fundamentals, pre-treating the data sets, creating models with MVA, interpreting the statistical results, and finally identifying the limitations of the models.

Using this methodology, it was possible to use MVA to correlate roughly half of the variability in final paper quality with the refining operations. The upstream variables that were the most prominent in the models were: plate age; specific energy, including reject refining energy, which had to be calculated from other variables; refining consistency, which also had to be calculated; number of TMP lines in operation; and variability in motor load, as represented by the standard deviation. The case study thus yielded results that were not only statistically significant, but also physically interpretable with regard to known process fundamentals.

Because no single model was able to cover all process scenarios, it seems that some kind of adaptive controller would be required to automate the TMP refining process. To this end, it is possible to use PLS models to predict new Y values from new X values. However, there is an enormous change in the coefficients from one month to the next, in the order of several hundred percent. Planned experiments could help address this problem, but regardless of the process control application being considered, accounting for data lags, data filtering, and time averaging is critical to capturing the necessary dynamics.

CONDENSÉ EN FRANÇAIS

L'analyse multivariée (AMV) est une technique statistique de longue date, qui crée des modèles linéaires à partir des variables existantes. L'objectif est de simplifier le système en créant des 'composantes principales' qui captent le plus possible la variabilité dans les données initiales.

Grâce à la révolution informatique, l'AMV est maintenant utilisée couramment dans l'industrie pour diagnostiquer les problèmes, suivre les procédés, et contrôler les systèmes. Elle est facilement accessible via les logiciels commerciaux pour ordinateur personnel. Par contre, cette technique statistique aux moindre-carrés demeure très susceptible à la devise « garbage-in/garbage-out ».

Les données de production sont souvent assujetties aux valeurs aberrantes, à la dérive des instruments, et aux arrêts et aux départs d'unités d'opérations, et l'échantillonnage des produits est souvent peu fréquent. En plus, l'AMV est une technique linéaire, tandis que beaucoup de phénomènes de procédé sont non linéaires. Pour l'ingénieur chimiste, la combinaison des informations provenant de plusieurs lignes de production en amont, pour faire un seul modèle cohérent du procédé global, représente un autre défi quand on fait ce genre de modèle « boîte noire ».

La clientèle du secteur des pâtes et papiers, comme celle de bien des industries globalisées, exige de plus en plus un meilleur produit à un prix plus compétitif. L'analyse de la vaste quantité de données sur les procédés et sur les produits qui sont accumulés dans les serveurs informatiques représente une stratégie importante pour atteindre cet objectif. Les procédés papetiers sont, de nature, multivariés, c'est-à-dire que les interactions entre les variables sont tout aussi importantes que les variables elles-mêmes. Pour en extraire le bénéfice maximal, il faut donc modéliser ces variables en groupes, en utilisant une méthode comme l'AMV.

En prenant comme étude de cas une usine de pâte thermo-mécanique (PTM) dans l'Est du Canada, nous avons d'abord comparé plusieurs méthodes de sélection et de prétraitement des données brutes pour maximiser le réalisme et l'utilité des modèles AMV, en éliminant par exemple les périodes d'interruption de production.

Nous avons tiré une conclusion importante : les modèles générés avec la variante de l'AVM connue sous le nom « Partial Least Squares » (PLS) ont été améliorés en prétraitant les données, non seulement par rapport à leur signification statistique, mais également en termes de leur interprétation physique. Nous avons donc recommandé une approche globale pour l'application de l'AMV aux données d'opérations industrielles, incluant une méthode systématique pour enlever les périodes

d'opération questionnables comme la production à la baisse ou les comportements aberrants, ainsi que le filtrage de toutes les variables.

Le prochain défi était de développer une méthode pour corréler les opérations PTM à la qualité de la pâte et, ultimement, au papier. Pour ce faire, nous avons mis l'emphase sur les principes fondamentaux tels l'énergie spécifique et l'intensité de raffinage. L'usine dont il est question subit des variations importantes dans la force et la porosité du papier bien connus pour être affectés par les conditions de raffinage de pâte en amont. Les interruptions fréquentes des lignes de raffinage font varier énormément l'énergie spécifique et d'autres paramètres clés, dont plusieurs ne sont pas mesurés directement et doivent être calculés à partir des mesures existantes.

À cause de la basse fréquence des mesures, il est difficile d'établir le lien entre les variations dans les propriétés du papier et les caractéristiques de la pâte tels l'indice d'égouttement, la longueur de fibre, et le contenu en matières fines. Pourtant, les lignes de raffinage sont riches en termes de données, avec de nombreuses variables qui sont mesurées chaque seconde. Malheureusement, les données de qualité des copeaux de bois étaient extrêmement limitées et peu fréquentes, et ont très peu contribué aux modèles AMV.

Une section importante, et parfois oubliée, de toute usine PTM est le raffinage des rejets. À l'usine que nous avons étudiée, le taux de production aux presses, ainsi qu'aux raffineurs de rejets, change continuellement parce que l'usine a souvent des arrêts et des départs sur les quatre lignes principales de raffinage,. Pour compenser, les opérateurs vont augmenter le taux de rejet quand une ligne est arrêtée, de 30% à 40% environ, ce qui fait changer la distribution de longueur de fibres de la pâte envoyée aux rejets. Cette situation, en combinaison avec les arrêts occasionnels des raffineurs de rejets eux-mêmes, mène à un raffinage de rejets qui est très variable et moins bien contrôlé. À titre d'exemple, à l'intérieur d'un seul mois, l'énergie spécifique de raffinage des rejets peut varier entre 800 kWh/t et 1400 kWh/t environ.

En utilisant l'AMV et d'autres outils statistiques, il a été possible de relier la qualité du produit aux opérations de PTM et de rejets, en tenant compte du nombre de lignes en opération, de l'âge des plaques, et des délais de procédé. Nous avons comparé trois échelles de temps : 1 heure, 8 heures et 24 heures. Les meilleurs modèles ont été obtenus sur une échelle de temps plus courte (1 heure), avec un filtrage à moyenne pondérée pour aider à combler l'écart entre les mesures d'opération rapides et les mesures de qualité lentes.

Puisqu'aucun plan expérimental n'a été utilisé, car non pratique dans ce cas, il est possible que certaines corrélations soient attribuables à la coïncidence. Nous avons donc ajouté et enlevé différentes variables et périodes de temps des modèles, pour mieux explorer leur validité.

Finalement, nous avons développé une méthodologie détaillée et explicite pour l'application de l'AMV aux données de production, à partir des résultats énumérés ci-dessus. Pour résumer, la méthodologie consiste à :

1. définir les objectifs de la modélisation, surtout l'utilisation du modèle (diagnostic, suivi, contrôle) ;
2. examiner les données de production, surtout les données de qualité du produit final, pour s'assurer que les tendances importances y sont bien représentées ;
3. choisir une échelle de temps, sur la base de la disponibilité des données, mais également en tenant compte de la dynamique connue du procédé ;
4. créer une structure de modèle basée sur les principes fondamentaux ;
5. enlever les valeurs aberrantes incluant les périodes de production à la baisse ;
6. synchroniser les variables entre elles ;
7. combiner les lignes en amont, pour créer un modèle global du procédé ;
8. appliquer un filtre à moyenne pondérée, pour éliminer le bruit, mais également pour simuler la dynamique du procédé ;
9. modéliser le produit intermédiaire, à partir des variables de procédé en amont ;
10. modéliser le produit final ;
11. interpréter les résultats statistiques par rapport aux principes fondamentaux ;
12. identifier les causes possibles de la variabilité dans la qualité du produit final ; et
13. identifier les limitations du modèle, pour éviter le plus possible les résultats fondés sur la coïncidence.

En suivant cette méthodologie, il a été possible d'utiliser l'AMV pour corréler environ la moitié de la variabilité dans la qualité du papier final aux opérations de raffinage. Les variables en amont qui se sont avérées les plus marquantes sont l'âge des plaques, l'énergie spécifique (incluant l'énergie du raffinage des rejets), la consistance de raffinage, le nombre de lignes PTM en opération, et la variabilité de charge des moteurs représentée par l'écart-type.

Le cas d'étude a donné des résultats qui étaient non seulement significatifs statistiquement, mais qui étaient également interprétables par rapport aux principes fondamentaux du procédé. De meilleurs résultats seraient peut-être possibles si les mesures en ligne étaient plus nombreuses, notamment pour la qualité des copeaux et pour la consistance de raffinage des rejets.

La méthodologie pourrait se généraliser à d'autres procédés industriels où l'on retrouve une matière première mal caractérisée, de multiples lignes de production, des arrêts et de départs fréquents d'unités d'opérations, et un échantillonnage peu fréquent des produits intermédiaires et finaux. Voici quelques unes de nos recommandations:

- L'AMV étant une technique aux moindre-carrés, nous recommandons de prétraiter les données tel que décrit ci-dessus. Les délais de procédé doivent notamment être synchronisés auparavant, sinon l'algorithme va comparer des périodes de temps non reliées.
- Le choix d'échelle de temps doit tenir compte de l'objectif global de la modélisation. Il est important de caractériser quelles sources de données sont « riches » avec de nombreuses variables fréquentes, et lesquelles sont « pauvres », limitées aux échantillons instantanés et peu fréquents.
- Quelque soit le type de contrôle de procédé envisagé, il faudrait tenir compte des délais de procédé, du filtrage, et des moyennes dans le temps pour bien capter la dynamique du procédé.
- Puisque l'AMV est une méthode mathématique linéaire, il est important de s'assurer que les variables sont choisies et les combiner ensemble de sorte que les principes fondamentaux du procédé soient le plus possible représentés . Pour le cas d'étude, nous avons mis l'emphase sur les notions de l'énergie de raffinage, l'intensité de raffinage, la consistance de raffinage, et l'âge des plaques.
- Il faut faire attention en interprétant les résultats AMV, par exemple, en insistant trop sur les relations cause-et-effet. C'est doublement vrai pour les systèmes avec des boucles de contrôle.

Étant donné qu'aucun modèle n'a pu couvrir tous les scénarios de production, il semblerait qu'un contrôleur adaptatif serait requis pour automatiser le procédé de raffinage PTM. Il est possible de représenter un modèle PLS sous la forme d'une équation de régression classique, et donc de prédire de nouvelles valeurs Y à partir de nouvelles valeurs X. Par contre, il y a une variation énorme entre les coefficients d'un mois à l'autre, en pourcentage de l'ordre de plusieurs centaines. Ce serait préférable d'avoir différentes séries d'équations pour chaque scénario d'opération connu, par exemple de nouvelles plaques, sinon les changements abrupts pourraient perturber de façon trop importante le contrôleur. Notre expérience avec les données nous fait croire qu'il faudrait mettre à jour les coefficients au moins une fois par jour pour bien suivre le procédé.

Aucun test à l'échelon ou sur le plan expérimental n'a servi pour générer nos modèles qui ont été construits entièrement sur la base de données de production existantes. Il est donc impossible dans tous les cas de savoir si chaque variable a bien été représentée. Prenant comme hypothèse que des expériences planifiées pourraient répondre à cette question, il faudrait tout de même bien capter les caractéristiques temporelles du procédé. L'objectif serait d'appliquer les délais et le filtrage aux variables pour simuler en quelque sorte la dynamique du procédé, pour qu'elles soient bien synchronisées entre elles et, encore plus important, avec les propriétés du papier final.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

LIST OF SYMBOLS AND ABBREVIATIONS

AQC:	Advanced Quality Control
ANN:	Artificial Neural Network
BDT:	Bone Dry Tons
CD:	Cross Direction
CPI:	Chemical Process Industry
CSF:	Canadian Standard Freeness
DCS:	Distributed Control System
DIP:	De-Inked pulp
DModX:	Distance to Model for X variables
DModY:	Distance to Model for Y variables
EWMA:	Exponentially Weighted Moving Average
GW:	Groundwood
HDP:	High Density Pulp
PI:	Process Integration
MD:	Machine Direction
MIMO:	Multiple Input Multiple Output
ML:	Middle Lamella (bond between fibres, mostly lignin)
MPC:	Model-Predictive Control
MVA:	Multivariate Analysis
NIPALS:	Nonlinear Iterative Partial Least Squares
ODE:	Ordinary Differential Equation
P:	Primary Wall (fibre layer containing fibrils in lignin-hemicellulose matrix)
P200:	Percent of fibres smaller than 200 mesh
PC:	Principal Component
PCA:	Principal Component Analysis
PDE:	Partial Differential Equation
PLS:	Projection to Latent Surfaces (or Partial Least Squares)
RI:	Refining Intensity
RMS:	Root-Mean Square
ROCE:	Return on Capital Employed
RTO:	Real-Time Optimisation

S1:	Outer Seconday Wall (fibre layer containing fibrils in helical structure)
S2:	Middle Secondary Wall
S3:	Inner Secondary Wall
SEC:	Specific Energy Consumption
SEM:	Scanning Electron Microscopy
SPE:	Squared Prediction Error
TEA:	Tensile Energy Absorption
TSI:	Tensile Stiffness Index
TMP:	Thermo-Mechanical Pulp
UHYS:	Ultra-High Yield Sulphite Pulp
UV:	Unit variance
α:	Weighting factor for moving-average filter
β:	Regression coefficient
τ:	time constant

CHAPTER 1.0 INTRODUCTION

1.1. Problem Statement

Existing Canadian newsprint mills must deal with ramifications of design decisions made in the past, when energy was cheap, water was limitless, and mills had total control over wood chip supply. Energy has become expensive, there are environmental limits on water use and discharge, and wood supply is largely outsourced to independent sawmills for whom chips are merely a secondary by-product of lumber.

Thermomechanical Pulp (TMP) mills are the main source of newsprint in Canada, which is an important export product. Unlike other products, such as molten metal, newsprint cannot be melted down and homogenised. Paper is made in real time, such that the sheet contains the history of the process. Variability is therefore a major problem; with regard to paper strength, it is the weak link that determines whether the sheets will tear during printing, thereby losing customers and ultimately eroding the competitive position of Canada's industry.

Due to globalisation, Canadian pulp and paper companies face increasing demands for better and more consistent product quality, with a simultaneous expectation of improved Return on Capital Employed (ROCE). Final paper quality is affected by seasonal variations, changes in incoming chip quality and other external factors that are often beyond the control of the mill operator, but also by many internal factors that are controllable, such as material flowrates, equipment settings, and the application of mechanical energy. However, in order to design an automated controller that would use real-time data to improve the process, we must first understand the inferential relationships between the process variables.

The process challenges faced by many Canadian mills newsprint mills include:

- Little or no measurement of incoming wood chip quality.
- Little or no buffering capacity for incoming chips.
- Frequent starts and stops of refiners, due to capacity mismatch relative to papermaking section, or to exploitation of lower off-peak energy prices.
- Infrequent pulp quality measurements, limited to only a few parameters.
- Limited pulp buffering capacity upstream of the paper machines.
- Paper quality that is highly susceptible to variations in raw material quality.

1.2The purpose of this doctoral project was not to eliminate these industrial problems, which are often built into the design of the mill. Rather, the goal was to identify ways to compensate for them, through the exploitation of existing data, to create knowledge about process operations. Most Canadian mills now have high-speed data historians into which are fed virtually all process and operating data for the entire facility. These thousands of data 'tags' (instruments or measurement points), some updated every few seconds, represent millions of new values each day. Most of these data are never used. Mill personnel can try to establish relationships between the process variables by considering only a few at a time, but this is an impossible task due to the inherent inter-relatedness of the variables. Multivariate Analysis (MVA) has emerged as one way to address this data explosion, because its automated pattern-recognition techniques are well-suited to detecting useful patterns and relationships in large datasets.

1.2. Objectives

The research topic for this doctorate is "Inferential Relationships in Thermomechanical Pulp Refining, Explored Using Multivariate Analysis". The background to the hypothesis is as follows:

> *"Empirical statistical techniques such as MVA have been employed with mixed success in the pulp and paper industry for such applications as TMP refiner control and paper quality. The specific approaches by different investigators vary, and are not well-described in the literature. It is unclear which non-linear first-principle relationships and fundamental models, if any, have been incorporated into the model development, nor whether the spatial and temporal characteristics of data have been systematically accounted for."*

The hypothesis itself is made up of three parts:

> *"By incorporating fundamental relationships and understanding the spatial and temporal implications of mil data, MVA-based process models of the TMP and papermaking processes can be developed that reflect measured process variability in a case study context. The process models can be of good quality, and not require extensive process testing such as bump tests and designed experiments.*
>
> *"Using Q^2 and other measures of success for the MVA-based models, a general and systematic procedure can be expressed based on the case study results.*

"If correctly developed and interpreted, the MVA-based process models can be useful for process troubleshooting and process control applications."

The case study used is a Thermomechanical Pulp (TMP) mill in Eastern Canada, with conical refiners and a feedstock of mainly black spruce and balsam fir. The overall project objective was to create a step-by-step, methodical approach for carrying out MVA on TMP operating data, while linking the statistical results with the underlying chemical and physical phenomena.

The main objectives were:

1 Basic Model Structure: To identify which combination of variables yields the best MVA models for key pulp characteristics in a single TMP line, taking into consideration known process relationships such as specific refining energy, refining intensity and plate wear in the TMP mainlines and rejects.

2 Data Pre-Processing: To improve multivariate analysis results by using systematic methods to deal with noise and outliers when extracting and pre-treating compressed historical data.

3 Modelling the Entire Mill: To establish a method for integrating different production lines together, in a way that incorporates process lags and addresses the problem of frequent starts and stops of the different TMP lines, and uses appropriate techniques such as weighted-average filtering to bridge the gap between frequent (refining operation) measurements and infrequent (pulp and paper quality) measurements.

4 Dealing with Process Dynamics: To determine the timescales, or combination of timescales, that give the most appropriate MVA models for linking the upstream TMP refining operations, intermediate pulp quality, and final paper quality.

5 Limitations of MVA technique: To characterize the limitations of MVA when applied to historical operating data, in the context of the case study application, but also in the more general context.

6 Overall Methodology: To develop a structured overall methodology that optimizes the potential for achieving good MVA results for troubleshooting product quality variations at a TMP newsprint mill.

A detailed project methodology is provided in Chapter 3, including sub-hypotheses and expected contributions to knowledge.

CHAPTER 2.0 LITERATURE REVIEW

2.1. Multivariate Analysis

Many sectors now face the problem of accumulating too many data for one person to absorb. Human beings can generally only visualise two or three dimensions, which is inadequate for systems with dozens or hundreds of inter-related variables. The advancement of computer technology has caused us to become "data rich, but knowledge poor" (Fayyad, 2001), and has led to the new field of data mining, whose purpose is to find useful knowledge in large databases.

In the Chemical Process Industry, the chief example of this problem is time-series operating data. Hidden within large databases are interesting relationships between process variables, which could serve to answer questions and guide decisions (Harmon and Schlosser, 1999). Of course, simply having a large number of data is no guarantee. Industrial data may contain the wrong type of information, for instance plentiful measurements on incidental equipment while other more critical process values go unmeasured.

Several "black-box" techniques are available to address this problem, which do not use first principles but rather search for patterns in the raw process signals. The most prevalent are listed in Table 2.1 (Shaw, 1999).

In pulp and paper, Multivariate Analysis (MVA) and Artificial Neural Networks (ANN) have been proposed for numerous applications, notably to create 'soft sensors' capable of filling in process values between real measurements, or to estimate parameters that cannot be measured directly (Ingman, 2000). One reported disadvantage of ANN is the inability to extract process insight from the results.

Table 2-1: Black-Box Modelling Methods

Black-Box Method	**Principle of Operation**
Artificial Neural Networks	Computer algorithm mimicking interactions between neurons in the brain
Multivariate Regression	Statistical regression technique, in which Y variables are modelled directly on X variables
Multivariate Analysis (PCA, PLS)	Indirect regression technique, in which a small number of new "components" are created from the original variables
Decision Trees	Series of logical operations that assigns probabilities to various process outcomes
Genetic Algorithms	Computer algorithm mimicking Darwinian evolution, where "populations" of possible outcomes compete for survival
Bayesian Networks	Directed graphical model, with nodes showing dependence relations among the variables.
Markov Networks	Similar to Bayesian Networks except that model is undirected
Fuzzy Logic	Extension of Boolean logic, in which binary values are replaced with degrees of truth
Cluster Analysis	Statistical technique for differentiating observations into groups, using similarity coefficients based on distance between points

In contrast, MVA is a purely statistical technique that offers a window into the inner workings of the process. While also a black box, it relies on fundamental statistics to reduce the dimensionality of the data space in a rigorous and systematic way (Johnson and Wichern, 1992). In CPI applications, the new dimensions or "latent variables" can often be associated with the fundamental chemistry and physics of the system at hand (Bharati, et al., 2003; MacGregor et al., 1991). This ability to fit a model using a small number of latent variables is the result of these process relationships, and not inherent to the MVA method itself (Kresta 1994). Of course, the model captures *all* of the variation when the number of components equals the number of original variables, but this is a trivial result; the user must boil them down to a lower dimensionality for the technique to be worthwhile.

The more familiar 'Multivariate Regression' does not include any latent structure. The standard model is given as follows (Burnham et al., 1999):

$$\mathbf{Y} = \mathbf{X}\mathbf{B}^T + \mathbf{E},$$

Where,

$\mathbf{X}$ is an $(n \times k)$ matrix of values for the independent variables;

Y is an $(n{\times}m)$ matrix of values for the dependent variables;

B is the $(k{\times}m)$ matrix of regression coefficients to be estimated;

E is the $(n{\times}m)$ matrix of random errors.

Multivariate regression requires that all variables be uncorrelated (i.e., statistically independent) and that the data be free of error (Nobleza, 1997). The X variables are assumed to be fixed, known constants. These are impossible conditions when using real process data, since many variables are highly correlated due to process interactions or the actions of control systems, and measurement error is commonplace.

MVA does not have these limitations. First proposed over a century ago by Karl Pearson (Pearson, 1901), the basic concept behind MVA is quite straightforward. However, it was only the advent of modern computing power that has made it possible to apply this technique to millions of data points. MVA addresses both latent structure and measurement error, because it seeks to plot the original data on an entirely new set of data-driven coordinates, rather than simply model Y directly from X. It falls into two main categories, Principal Component Analysis (PCA) and Projection to Latent Surfaces (PLS). They differ in that PCA treats all variables as equivalent, whereas PLS distinguishes between X and Y variables (Eriksson et al., 2001). The following summarizes when to use PCA versus PLS:

- PCA is used to give an overview of the data set, to identify outliers, or to transform complex signals into a more useful form (e.g., spectroscopic analysis). It is very susceptible to modelling uninteresting correlations; a large number of variables which move up and down simultaneously with, say, throughput will yield a strong but trivial model.
- PLS is used when there is an expected dependent/independent relationship among the variables. PLS is also used when some of the most important variables are sparse or few in number, and would otherwise be diluted by all the other variables. PLS is less likely to yield trivial results; not only must there be correlations within each of the X and Y spaces but, crucially, there must also be a relationship between each pair of X and Y components.

In both cases, a new set of orthogonal coordinates or 'components' is created which captures as much as possible of the variation present in the original dataset, hopefully at a much lower dimensionality. PCA works by finding the dimension vector which explains as much X-variation as possible (Eriksson et al., 2001). This becomes the first component. The algorithm then finds a second component which is orthogonal to the first, and explains as much as possible of the remaining X-variation. The process continues until the researcher is satisfied or the incremental increase in explanation is judged minimal. Essentially, PCA generates a new set of axes that match the dataset better than the original coordinates did. Datapoints can then be projected onto the hyper-planes defined by the components, to yield two-dimensional plots and other useful outputs.

In mathematical terms, PCA is a linear model that operates as follows (Johnson and Wichern, 1992):

⇒ Consider an (n x k) data matrix **X** *(n observations, k variables).*

PCA models this as *(assuming normalised data):*

$$\mathbf{X} = \mathbf{T}\mathbf{P}^{T} + \mathbf{E}$$

Where,

T $(n \times m)$ is the scores of each observation on the new components;

P $(m \times k)$ is the loadings of the original variables on the new components;

E $(n \times k)$ is the residual matrix, containing the noise.

The product of the score vector and the loading vector is referred to as the 'Principal Component' or PC. While this equation may resemble that for Multivariate Regression, it differs significantly in that the T and P matrices are entirely new creations representing the latent structure. The T values, or 'scores', are the new co-ordinates of each observation as projected onto the PC. For time series data, the score vector represents the value of the newly created latent variable at different points in time. The P values, known as 'loadings', are the weights assigned to each original variable by the PCA model. More precisely, the loading is the cosine of the angle between the PC and the original variable axis. Thus the larger the loading, whether positive or negative, the more closely that variable is related to the PC.

To equalise the impact of variables with different orders of magnitude, the variables are normalised beforehand to have a mean of zero, and a standard deviation of one. The combination of unit variance (UV) scaling and mean centring is commonly referred to as autoscaling (Eriksson, 2001). For some applications it may be undesirable to normalise the data, such as for spectroscopic analysis, but for process data it is routine because of the presence of different engineering units.

The classical approach to computing components is based on eigenvector and eigenvalue theory, and is often referred to as the kernel algorithm. The eigenvectors of the original X correlation/cross-correlation matrix give the coefficients of the PC's, while the eigenvalues give the variance of each new PC (Johnson and Wichern, 1992). With the kernel algorithm, all possible principal components are computed at the same time. This can be computationally intensive, especially since only the first few components are typically required to model the system; higher components often represent just noise or other uninteresting results. Modern software packages therefore use a numerical method known as Nonlinear Iterative Partial Least Squares. The NIPALS algorithm has the added advantage that it can accommodate datasets with missing values (Eriksson, 2001). Note that MVA does not require a multivariate normal assumption for the original variables (Johnson and Wichern, 1992), yet another advantage over multiple regression.

PLS provides a predictive equation for Y in terms of X by finding a set of orthogonal components that maximises the level of explanation of *both* X and Y. This is done by fitting a set of components to X as in PCA, doing the same for Y, and then reconciling the two sets of components to each other. Thus Y is not modelled directly from X, but indirectly via the latent structure; one reported advantage is that PLS does not over-fit the data like ordinary regression models (Kresta, 1994). In mathematical terms PLS is described as follows (Johnson and Wichern, 1992):

$\mathbf{X} = \mathbf{TP}^{\mathbf{T}} + \mathbf{E}$ outer relation for X *(like PCA)*

$\mathbf{Y} = \mathbf{UQ}^{\mathbf{T}} + \mathbf{F}$ outer relation for Y *(like PCA)*

$u_h = b_h t_h$ inner relation for components

Where,

X is an $(n \times k)$ matrix of values for the independent variables;

T $(n \times m)$ is the scores of each X observation on the new components;

P $(m \times k)$ is the loadings of the original X variables on the new components;

E $(n \times k)$ is the residual matrix for X, containing the noise.

Y is an $(n \times l)$ matrix of values for the dependent variables;

U $(n \times q)$ is the scores of each X observation on the new components;

Q $(q \times l)$ is the loadings of the original X variables on the new components;

F $(n \times l)$ is the residual matrix for X, containing the noise;

b_h is the regression coefficient.

The term b_h is the regression coefficient for component number h. A plot of t_h versus u_h for each component gives a visual representation of the correlation structure between the X-space and the Y-space. The algorithm tweaks the X and Y models to optimise this inner relation, yielding new parameters (w* and c) known as the 'variable weights' which play the same role as PCA loadings. As shown above, the inner relation is normally a linear function, although the use of non-linear equations is also possible (Zamprogna et al., 2002).

Commercial software uses an iterative algorithm which converges on the best MVA solution. For PLS, it is a multiple iteration as illustrated in Figure 2.1 (Ericksson et al., 2001):

- find best PCA solution for **X**;
- find best PCA solution for **Y**;
- reconcile the two PCA solutions using the inner relation to obtain the best PLS solution.

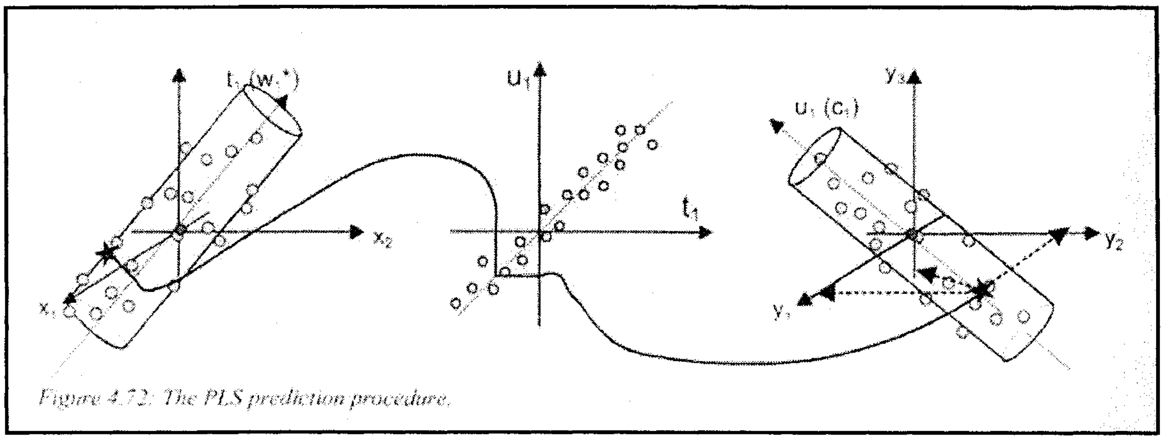

Figure 2-1: Three PLS equations solved simultaneously by iteration (Eriksson et al., 2001).

PLS models serve to maximize the covariance between a set of X variables and a set of Y variables. These are mathematical, not physical, distinctions: the decision as to whether a given variable is included in the X set or in the Y set is entirely up to the PLS user. Cause-and-effect relationships cannot be automatically assumed for X and Y in PLS (Johnson and Wichern, 1992). Such relationships can only be determined using designed experiments, a condition not usually satisfied when dealing with raw process data.

2.2. Paper Strength and Pulp Quality

Most of the newsprint in Canada is produced from virgin wood using thermo-mechanical pulping (TMP). It is so named because of two main steps: pre-steaming, to remove entrained air from the wood chips and induce lignin softening; and mechanical refining (Sidhu 2004). The chips are washed beforehand to remove debris, to warm and soften the chips, and to regularise the moisture content prior to primary refining. The specific energy required to make TMP pulp in two-stage refining is in the order of 2 000 kWh/t (Smook, 1982).

To be useable, newsprint must have certain characteristics. The first is strength, which in newsprint is all important, given that the product must withstand tensions within the paper drying section at the TMP mill, and later in the customer's printing lines. There are numerous strength parameters for newsprint, listed in Table 2.2. Another key characteristic is the paper's ability to retain ink. The newsprint must have the proper resistance to liquid penetration, to limit spreading and prevent wicking (Lyne, 1991). A benchmark measurement for this property is porosity, often expressed as permeability to air flow.

Table 2-2: Pulp and Paper Quality Parameters Relevant to Research Project

Parameter	**Units**
THERMOMECHANICAL PULP	
Canadian Standard Freeness	mL
Average (length-weighted) fibre length	mm
Fines content, defined as small enough to pass through 200 mesh screen (76 μm)	% (mass)
NEWSPRINT	
Tensile Stiffness Index	kNm/g
Burst Strength	kPa
Tear Strength	mN
Rupture Strength	kN/m
Tensile Energy Absorption	J/m^2
Stretch	%
Permeability to air	mL/min
Linting	%

Paper is a bonded fibrous network, composed mainly of cellulose, the world's most abundant biopolymer (Mark, 2001). Early work on paper physics was therefore borrowed from the textile industry (Dodson, 1973). It has been claimed that the total performance of paper products can be reduced to the question of how moisture and temperature interact with wood polymers on a molecular level (Salmén, 1991). The strength of a wood fibre has been found to be approximately 20 times that of the strength of an inter-fibre bond (Niskanen, 1998), which has led some researchers to declare that "paper is hydrogen bonds" (Pawlak, 2003). Nonetheless, in tensile failure as much as 55-65% of fibres are actually broken, as demonstrated in the landmark paper by Van den Akker et al.

(1958). In other words, both fibres and fibre-to-fibre bonds are broken in the fracture of normal papers (Dodson, 1973).

Stretch, burst and tensile strength are all related to the degree of bonding. The overall strength of the bonds is determined not just by available bonding area, i.e., the area of fibre crossing, but also by the fraction of that area in actual contact, which is 40-45% for unbeaten fibre and 70-75% for beaten fibre (Pawlak, 2003). At a single fibre-to-fibre bond in paper, there may be as many as 10^8 hydrogen bonds (Dodson, 1973). Hydrogen bonds are directional, form quickly, are readily reversible, and have energy lying partway between those of covalent bonds and van der Waals forces (Niskanen, 1998).

Wood fibres are strong in tension, but weak under longitudinal or axial compression due to their helically wound fibrillar structure. This is important, because fibres in wood undergo axial compression during chipping, screw pressing and plug-screw feeding. They are further exposed to bending and axial compression in pulp during pumping, mixing, dewatering and refining. These deformations are later set during pulp drying, potentially affecting the final paper properties (Seth, 2006).

Strength variability is as important as absolute strength; an acceptable average strength with a large standard deviation may still mean there are local spots that are insufficiently strong. Attaining quality targets is critical to ensuring the weakest link does not fail, but reducing overall variability is equally critical. Rheologically, paper has a long memory of its past history (Dodson, 1973), and cannot be homogenised like a molten metal. Downstream customers adjust their printing lines to accommodate the paper being used; changing characteristics can therefore lead to paper breaks, poor printing quality and other problems.

Variation occurring at different frequencies corresponds to different levels of operation or control. Notably, variations occurring in the 10 s to 10^{-2} s range must be addressed during design, and cannot be compensated for later by the process controllers (Sell, 1995). This is critical for TMP mills, since the residence time for a refiner falls within this range.

Another important newsprint characteristic is linting, the loss of small particles from the paper surface. Amiri et al. (2003) describe an on-line device to measure Pulp Linting Propensity Index (PLPI), an indicator of the quantity of ray cells, fibre fragments and shives in a paper sheet. The authors found that linting was reduced by more uniform refining and higher specific energy.

Final paper quality is directly impacted by intermediate pulp quality. Saltin and Strand (1995) found that length-weighted fibre length was a critical factor to tear strength. For TMP, there is usually a compromise between fibre length which is good for strength properties, and cut material which is good for optical properties such as opacity (McDonald et al., 2004). Pulp quality is influenced by many factors, including quality of the wood chips, pattern and wear of refiner plates, refiner consistency, specific energy, plate gaps, and refining pressure and temperature (Metso, 2002). Foremost among these is incoming chip quality, which is in turn affected by initial tree characteristics, harvesting techniques, transportation methods and chipping operations, and other upstream factors (Wood, 2001). The content of knots, rotten wood and dust in the incoming chips can also impact pulp quality. Chip size is, however, much less important in mechanical pulping than in kraft pulping, where a wide chip size distribution leads to wide variations in impregnation effectiveness.

According to numerous authors, the single most important factor for pulp strength is wood species (Rudie and Sabourin, 2002; Begin and Amiri, 2002; Marklund et al.., 1998; Yi et al.., 2005). Sabourin et al. (2003) found that the morphological properties of a given wood species had a major effect on pulp physical properties and specific energy consumption. For instance, paper produced from spruce/fir pulp had higher tensile strength than those from pine pulps. Also, pine pulps had to be refined to lower freeness to produce paper with comparable surface and printing properties.

In a five-year survey of European wood sources, Lundqvist (2003) found that improved wood and fibre use could offer large benefits in quality and efficiency. In particular, chips from pulp wood, especially from thinning, could improve optical properties, while sawmill chips, especially from large diameter timber, could improve strength properties.

Several on-line woodchip monitors are under development, though none is yet commercially available (Smith et al., 2004). PAPRICAN is reportedly developing a chip monitor that calculates size and shape distribution, based on digital imaging at the conveyor, but no details have been published. The CRIQ has issued several articles about their unit, based on a red-green-blue colour camera and near infra-red sensor, which they claim can help determine wood species and freshness under appropriate conditions (Ding et al., 2005; Bédard et al., 2003; Laperrière et al., 2004; Lanouette et al., 2003).

2.3. TMP Refiner Control and Operation

High-quality pulp requires long, well developed fibres that are well separated. Proper refiner operation is critical to this aim, to achieve maximum separation but minimum cutting of fibres. The residence time between refiner plates is typically 2-7 seconds. Most of the refining occurs when the bars are directly opposite one another, and most of the work is done fibre-to-fibre (Sidhu et al., 2004). Typical controlled and manipulated variables are shown in Figure 2.2 and in Table 2.3.

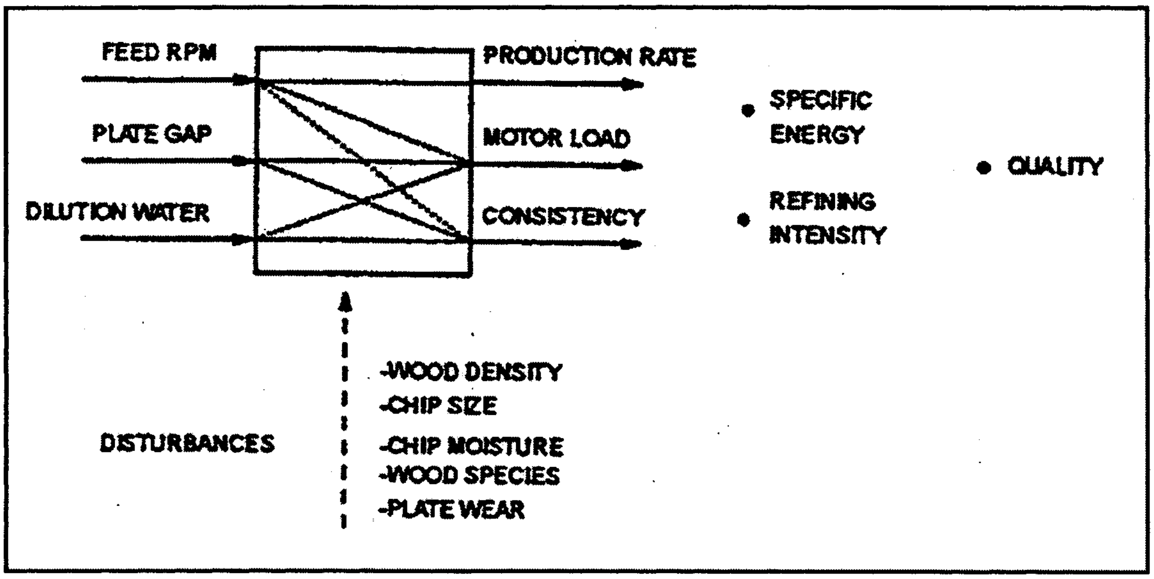

Figure 2-2: TMP Control Parameters, Roche *et al.* (1996).

Typically, TMP operators use freeness as the main indicator of pulp quality, adjusting the set points for transfer screw speed, plate position, and dilution water flowrate (Cluett et al., 1995). However, both Thode (1959) and Elsinga (2002) working over 40 years apart found that freeness was not a good measure of pulp quality, because it depends on fibre properties as well as size classification. Miles and Onholt. (2003) found that the specific energy required to reach a given freeness is related to amount of long fibre in the pulp. Modern control systems (e.g., Strand et al., 2001; Sidhu et al., 2004) therefore use both freeness and fibre length as indicators, generating a window within which the refiners should operate.

Table 2-3: Controlled and Manipulated Variables for Mainline TMP Refining

Manipulated Variables	
1	1° & 2° Plate Gap
2	Chip Feed Screw Speed (throughput)
3	1° & 2° Dilution Rates
Controlled Variables	
1	1° & 2° Consistency
2	1° & 2° Specific Energy Consumption
3	Freeness
4	Long Fibre content
Equipment Operating Parameters	
1	Plate specifications
2	Change cycle of plates
3	Disc rotational speed
4	Steaming temperature

For conical refiners, specific energy and freeness are mostly affected by, in descending order: consistency, production rate, conical gap and flat gap (Metso, 2002). Some key operating parameters are listed in Table 2.4.

Table 2-4: Key TMP Operating Variables - Conical Refiners – Mainline and Reject Lines

Variable	Unit
Motor load	MW
Production rate	t/d
Specific refining energy	kWh/t
Flat plate gap	mm
Conical plate gap	mm
Dilution flows	L/min
Steam pressure drop across refiner (ΔP)	kPa

Variable	Unit
Blowline consistency	% solids
Plate age	h
Reject rate	%

Four main forces are involved in high-consistency refining. Compression forces contribute mainly to the subdivision of the chips, whereas shear forces serve to fold and the fibres in order to make them more flexible. If the sum of these forces varies, there will be unstable refining (Metso, 2002):

1. Centripetal force generated by the rotation of the disc.
2. Drag created by generated vapour, both forward and countercurrent.
3. Friction between pulp and plate segments
4. Squeeze between plates

Reject refining, because it treats the longest fibres, can have a major impact on strength and other final paper properties. Croteau et al. (1993) found statistically significant relationships between reject refining parameters (consistency and specific energy) and downstream pulp and handsheet characteristics, which is very noteworthy considering that only 25% to 30% of pulp passes through the rejects. Interestingly, paper strength properties were not shown to be related to the pulp properties of the reject refiner stock, but this study was limited to bivariate statistics only.

Kangas et al. (2004) used Scanning Electron Microscopy (SEM) to study the surface morphology and chemistry of spruce wood during TMP refining. Lignin-rich flake-like fines and ray cells arose mainly during the first phases of refining, while fibrils containing more cellulose were formed later during the peeling of cellulose-rich inner fibre wall layers. Flakes are known to enhance the light-scattering properties of paper, while fibrils are important for strength properties. Fibrils originally released originated from outer fibre wall layers, mainly P and S1, but at later stages they were peeled off from the inner fibre wall layers (S2) as well. Fibrillar material was also generated during reject refining. The authors concluded that the flake-like fines formed during mainline refining probably consisted mainly of material from the middle lamella (ML) and primary (P) wall.

Pulp refining is a highly complex process using a biological feed material, so all fundamental models to date have been semi-empirical (McDonald et al., 2004). Miles and May (1993) were awarded the Wallenberg Prize in 1998 for their breakthrough in understanding the fundamental mechanisms of turning wood chips into fibre (May, 1998). They elaborated the concept of 'Refining Intensity' (Miles, 1998), the energy delivered per refiner bar impact; for instance, a plate with a coarser bar pattern has a higher refining intensity than with a finer pattern. This concept has provided a major impetus to improving quality and reducing energy consumption in the manufacture of mechanical pulps.

Excessive refining intensity can damage fibres, even when specific energy and freeness appear normal, leading to reduced fibre length and tear strength (McDonald et al., 2004). Refining intensity in the secondary stage has been shown to have a significant impact on softwood pulp quality (Miles and Onholt, 2003; Lama et al., 2004). It is generally desirable to have lower refining intensity in the second stage to avoid excessive fibre cutting. McDonald et al. (2004) found that by matching refining intensity to wood characteristics, it is possible to optimise energy application.

The most recent work has focussed on forces rather than energy. Kerekes et al. (2006) found a relationship between fibre characteristics and fractional bar coverage, which is the fraction of a bar length that is supporting force. In particular, the authors emphasise the importance of gap size and specific edge load, defined as the energy per bar crossing per unit length. These concepts help explain why refining coarse fibres, which require greater normal forces and therefore experience higher shear forces, leads to more surface fibrillation, fines and energy consumption.

McDonald et al. (2004) have proposed on-line control of refining intensity to minimise process variations, by manipulating consistency or refiner speed. Refining intensity is a roughly linear function of the disc rotational speed; the larger the plate, the higher the slope (Hsieh and Wang, 2005). Refining intensity for a fixed consistency was found to be proportional to the rotational speed squared (Miles and Onholt, 2003). These studies have been done on flat refiners; to date no refining intensity equations have been published for conical refiners.

When refining intensity is too high, the freeness is achieved through fibre cutting instead of fibre development, resulting in the type of gain reversion described by Owen et al. (1998) as shown in Figure 2.3 (dialogue boxes added). The authors found that for motor load regulation at TMP refiners, there was a rapid change in gain, both in sign and value, at a specific transition point.

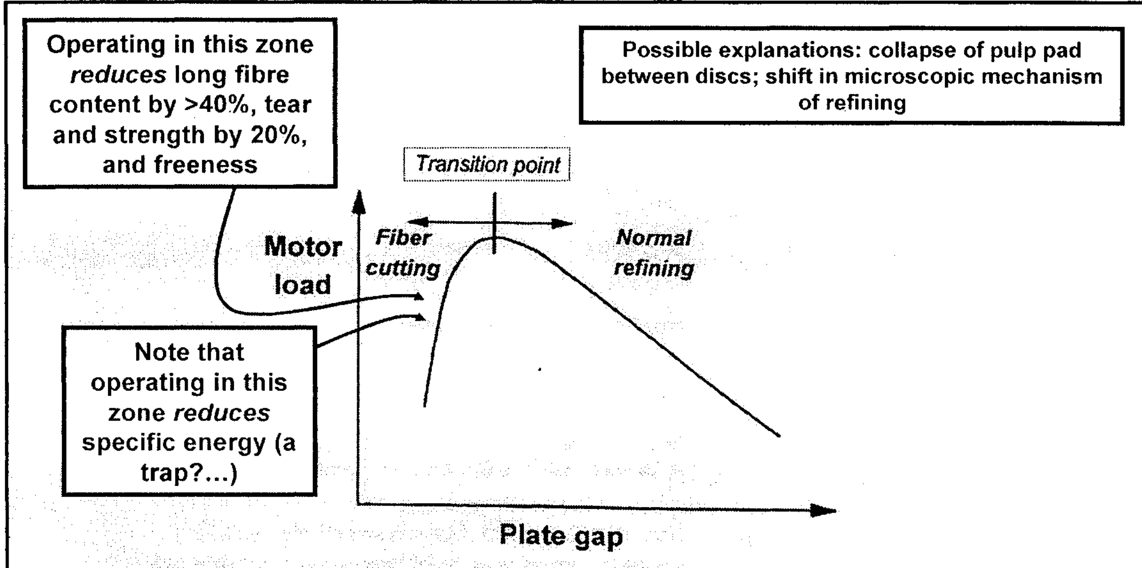

Figure 1. Motor load versus plate gap: As plate gap is decreased a transition point can be reached where the motor load drops rapidly and fibre cutting takes place.

Figure 2-3: TMP Motor Load Gain Reversion, modified from Owen *et al.* (1998).

Roche et al. (1996) found that TMP control schemes address specific energy, but not refining intensity, because it is too hard to measure fibre mass flowrate. The authors' main recommendation is to control motor load by manipulating feeder speed, and stabilise blow-line consistency. For a given plate configuration and disc rotation speed, refining intensity is largely a function of refining consistency. This is an inverse relationship, since greater consistency means a longer residence time between the refiner plates and hence more bar impacts for a given specific energy.

Miles and Onholt (2003) stated that TMP quality is more important than energy cost, yet the industry has focussed on reducing specific energy. The authors suggest that the real limitation is actually the inability to apply *enough* energy.

TMP refining tends to be controlled directly by the operators. Roche et al. (1997) did a survey of pulp quality sensors on TMP lines, and found that only 12% of them were being used for closed-loop control. There tended to be poor correlation between on-line and laboratory freeness, and the importance of instrument drift and calibration were often ignored.

The refiner plates have a normal lifespan of about 2000 hours, during which time the bars on the plate surface are gradually worn down, affecting the process dynamics. Less energy is required with an older plate, but the refining intensity is higher, because the plate gap is smaller resulting in a shorter residence time (Croteau et al., 1993). Plate age displays both slow and fast effects on the TMP refining process, because the plates wear down gradually over several thousand hours of operation, and then are abruptly replaced with new plates. Lama et al. (2006) reported the effect of plate age on a mathematical model of TMP motor load for a twin refiner. The authors attributed these gain changes to unbalanced forces affecting older refiner plates, where grooves are less deep providing less net space for steam to escape. The authors conclude with an overall recommendation to recalculate the gains each time the nominal operating conditions change.

The presence of fines in the furnish is considered to aid in bonding, but fines produce less strength than do the equivalent amount of whole fibres (Thode and Ingmason, 1959). Law (2005) stated that the importance of fines to TMP strength has been overlooked, and that most intact fibres are far less developed than was thought, meaning that fines do indeed contribute much to the overall bonding capacity. Unfortunately, the measurement of fines in pulp can be quite problematical (Seth, 2003).

The TMP refining process has some extremely fast and some very slow process dynamics. For example, the time constant of the model between the primary plate gap and the motor load is about two minutes, but the time constant between the primary plate gap and freeness is approximately ninety minutes (Sidhu et al., 2004). This large difference in the open-loop process bandwidth of the process was due to the location of the pulp quality monitor after the latency chest, such that the dynamics of the latency chest were lumped in the response of the quality variables. This is an example of a problem built into the design of the mill.

2.4. MVA Applications in the Pulp and Paper Industry

Many authors have reported that MVA, when applied to paper production, can boil down a large number of process parameters into a handful of meaningful latent variables (Strand et al., 2001; Broderick et al., 1995; Lupien et al., 2001; Saltin and Strand, 1995; Shaw, 2001; Nobleza, 1997; Winchell, 2005). Because of the nature or paper production, such black-box models are often appropriate; sophisticated first-principle models may be highly accurate, but pose difficulties due to the complicated mass and energy balances on which they are based (Alexandridis et al., 2002).

The three main applications of MVA in pulp and paper have been troubleshooting, process monitoring, and inferential or "soft-sensor" control using PLS models (Strand et al., 2001; Kooi, 1994; Kresta et al.., 1994). Even though the process may be highly non-linear, the use of a linear model like MVA is often justified because most industrial refiners are operated over a very narrow range of conditions (Cluett, 1995).

When using MVA on real process data, it is unrealistic to expect the type of goodness-of-fit one finds in laboratory experiments, where it is possible to achieve R^2 well over 90% using precise laboratory apparatus and an experimental design. Industrial models are much less precise, more in the range of 50% or so. According to Champagne et al.. (2002), a typical soft-sensor in the pulp-and-paper industry has 2-12 components explaining 40%-75% of the process variability.

Using daily averages, Saltin and Strand (1995) established the influence of certain TMP properties on paper quality with Factor Analysis (a variant of PCA in which the component directions are adjustable). In a previous study, the same authors had found five underlying phenomena that accounted for some 80% of the variation in newsprint quality: fibre bonding; fibre length; unbonded surface area; fibre orientation; and pressing. Using 100-150 variables, the 1995 study confirmed that fibre length had a strong influence on tear strength.

Nobleza (1997) performed PCA on monthly averages for furnish, refining energy and quality variables from four TMP refining lines. The major contributors to strength variations were found to be chip source and chip size distribution. The author states that relationships normally obtained through statistically designed experiments can just as easily be obtained from readily available mill data, but this statement is probably too optimistic since many key variables are artificially held constant by control loops and are thus invisible to the MVA technique.

Lupien et al.. (2001) used daily averages from a newsprint mill whose feed consisted of high-yield sulphite, groundwood (GW) and deinked pulps (DIP). The objective was to maximise Tensile Energy Absorption (TEA), tear strength and opacity. The parameters used included the proportion of each type of furnish. The authors expressed surprise at their main finding, namely that two-thirds of the strength variations were explained by paper machine variables. They attribute this to the fact that the paper machine data were based on 30-second scans, whereas the pulp parameters were based on only 4-6 lab analyses per day. This article highlights the extreme importance of considering the nature of each data source when interpreting MVA results.

Browne et al.. (2004) applied Factor Analysis to monthly and weekly averages from an Eastern Canadian TMP mill to establish relationships between furnish and pulp properties. A portion of the variability in pulp properties was explained by wood freshness, as measured by the potential brightness of the wood. When this potential brightness factor was high, typically in late winter or early spring, pulp brightness was higher and lower bleaching levels were required. Another portion of the variability was due to the ease with which energy could be applied to the wood. When this wood quality factor was high, typically in the summer months, tear strength also rose since higher levels of specific energy could be applied before the onset of fibre cutting.

Elsinga (2002) applied Factor Analysis to operating data from newly reconfigured refiners, following complaints from customers about paper linting. This paper differed in that planned experiments were performed, using a factorial design for feed rate, feed consistency and reject rate. This forced the process to behave under conditions that either might never have occurred, or that might have taken a long time to occur if waiting for random chance. The author claims that such an approach provides better, and quicker, results than simply using historical data.

Kooi (1994) created an inferential controller for wood chip refining, in order to predict the freeness in real time from dozens of other variables, rather than waiting for infrequent measurements from the latency chest. The controller could then adjust the manipulated variables, such as plate gap and water flow, using this inferred, instantaneous freeness value. The author concedes that this proposed method would not be able to detect changes in chip density or to correct for them. The controller is described as self tuning, but it does not appear to have ever been tested on a real refiner.

Various articles by Strand et al.. (1998, 2001, 2005) provide a series of examples of MVA-based soft sensors at North American TMP mills. Data from the wood yard, pulp mill process and paper machine were used, along with on- and off-line pulp and paper quality measurements. Consistency was predicted using a hybrid model, using mass and energy balances together with MVA. Specific energy was controlled using refiner plate gap, both in the flat and conical zones, with set points recalculated every time an on-line pulp quality sample was taken. The authors state that they introduced variability as a separate parameter in their MVA, by creating a new variable representing variance, but few details are given. They also favour the use of Root-Mean Square (RMS) for Cross-Direction (CD) and Machine-Direction (MD) tear strengths. Advanced control at TMP mills has reportedly shown a number of benefits, such as reduced freeness variation, reduced shive levels, improved energy usage, reduced paper quality variation, increased refiner plate life, and increased pulp strength. Under the new control regime, mill operators set pulp quality targets, instead of changing individual refiner plate positions, feed screw speeds, and refiner dilution flows.

The above papers reported a very wide range of timescales, from monthly, weekly and daily averages down to instantaneous readings (Nobleza, 1997; Lupien et al.., 2001; Saltin and Strand, 1995; Shaw, 2001; Strand et al.., 2001; Browne et al., 2004). None of these papers offered any explanation for the choice of timescale. In a non-TMP application, Bendwell (2002) justified the use of 24-averages based on the long retention times in pulp-and-paper wastewater basins, suggesting that the time constant of the system at hand should be considered when choosing a timescale. Rosen et al. (2001) recommends a multi-scale approach, to allow trends at different frequencies to be studied together.

Many authors report MVA applications for other pulp and paper systems, such as grade changes (Kuusisto et al., 2002), wastewater treatment plant control (Bendwell, 2002) and chemical pulping (Broderick et al.., 1993, 1994 and 1995; Wold and Kattenah-Wold, 2003). Ritala et al. (1991) report success at addressing the problem of uncontrollable fluctuations in wet-end chemistry using a computer-based diagnostic system for analysing different measured variables. Both PCA and PLS have been applied to paperboard production, using data from on-line and laboratory measurements (Ivanov, 2003). MVA has even been applied to the pulp and paper industry itself, using data from thirty different mills (Tessier et al.., 2001) to compare paper quality at mills with similar technologies.

Dayal et al. (1992) used ANN and PLS to develop an empirical predictive model for Kappa number. Historical plant data were used, without any form of experimental design, meaning that the technique depended on natural variation in the process to generate correlations. Roughly 44% of the process variation was captured. One reported disadvantage of ANN was the inability to extract any kind of process insight from the results.

Tessier and Broderick (2001) give several examples of MVA applications in pulp and paper, such as the optimization of chip size distribution for an Ultra High Yield Sulphite (UHYS) pulp plant, refiner pulp quality prediction and control, and the effect of refiner plate filing material on fibre development. In some cases the variables were manipulated in designed experiments. An earlier study by Broderick (1995) provided a graphical interpretation of PLS components for UHYS handsheet properties.

Shaw (2001) describes two projects, the first of which was to improve CD stiffness at an uncoated free-sheet machine while reducing cost. This data-driven optimisation project narrowed down dozens of variables to 10 parameters, finding results that were in some cases opposite to the prevailing wisdom at the plant. The second project, in the pulp mill, sought to increase production without compromising quality by achieving 100% hardwood use with no peroxide. In this case, 12 key parameters were identified from an initial 73. This paper underscores the importance of correctly selecting those parameters to be included in the MVA analysis, an important decision which from the outset will influence all results.

Croteau et al. (1993) applied time series techniques to analyse TMP operating data: cross correlation, coherence, and coherent power. Power spectra were used to verify the adequacy of the sampling interval. Their work highlights the importance of pre-conditioning data to deal with randomly missing values, irregularly spaced observations, or interruptions.

Champagne et al. (2002) created a soft sensor for process stability and product quality in an unspecified type of mill, which takes advantage of readily available data from the Distributed Control System (DCS) and paper testing laboratory. Interestingly, the authors compared neural networks and MVA for the same application, concluding that MVA was superior because it could indicate via the residuals when the model was no longer valid. MVA also offered the advantage that the contribution plots could immediately indicate the location of a problem, a key element in process monitoring.

Two different papers (Sarimveis, 2001; Phung, 2003) describe the creation of soft sensors for final paper characteristics that cannot be measured in real time, such as tissue softness and tear strength. Neural nets were reported to have had the best correlation but were difficult to interpret. Phung (2003) made several recommendations, notably to exclude outliers from the training set.

Using MVA applied to daily averages, Ortiz-Cordova et al. (2006) found significant correlations between TMP operating variables and final paper quality. To deal with grade changes, the authors recommend two approaches, namely to use an index when possible, otherwise to use only data for one specific basis weight.

2.5. Challenges and Limitations of the MVA Technique

Multivariate statistics have been used to understand and ultimately reduce process variation in a variety of industrial sectors (MacGregor et al., 1991; Mason et al., 2004; Kresta, 1994). MVA is clearly a powerful tool, but it remains a black-box statistical technique, entirely data-driven, and therefore highly susceptible to the problem of "garbage-in/garbage-out".

The MVA user is confronted with a series of inherent challenges, and must make decisions right from the start that will affect the final results. These challenges fall into three categories:

- Those requiring process knowledge or chemical engineering insight in order to be addressed, the most obvious being to select which variables to use among the hundreds available in a modern industrial plant;
- Those requiring statistical, mathematical, or data-oriented solutions; or
- Those that are unavoidable, but must nevertheless be understood to ensure proper interpretation of the final results.

A statistical analysis is only as good as the original data, and MVA tends to be slanted towards those variables which were measured better or more frequently, as seen in Lupien et al. (2001). When time series data are used, regardless of the type of process, the plots tend to 'snake' around the component space, indicating that the process is never really in steady-state (Kettaneh-Wold and Wold, 2003; Ivanov, 2003). Perfect steady-state data would be useless for MVA, of course, since none of the variables would be changing and hence there would be no correlations. This raises another key problem, which is that variations about steady-state can be relatively small, and may not be much bigger than the measurement error.

Hodouin et al. (1993) emphasise that an MVA model only works within the domain where it was calibrated, and Kresta (1994) reports that the process must continue to behave in a similar fashion as the original dataset. These limitations are true of any black-box model. One solution is to constantly and automatically update the model, i.e., make it adaptive (Rosen et al., 2001).

MVA is blind to variables that do not vary significantly, regardless of their actual physical importance. For instance, if the temperature in a chemical reactor is kept constant, it will not correlate with any other variable and will thus appear to be of no importance. Designed experiments can be used to counter this problem (Elsinga, 2002).

Browne et al.. (2004) caution that care must be used when interpreting and assigning cause-and-effect relationships to MVA results. Two unmeasured variables may be separate functions of a third, unmeasured variable. This is especially true of variables affected by control loops, where correlations found are often the exact opposite of reality, due to the action of the controller. Indeed, Hodouin et al. (1993) report that MVA models created under closed-loop conditions cannot predict open-loop behaviour, while Kresta (1994) reaches the complementary conclusion that open-loop data cannot be used to model closed-loop schemes.

Among the mathematical challenges of using MVA are the fact that it is a least-squares technique, and thus highly sensitive to outliers, whether caused by sensor malfunctions, start-up and shutdown of individual pieces of equipment, time lags, or other problems. MVA is likewise highly sensitive to instrument drift, since this can appear as a long-term trend to which the algorithm blindly ascribes statistical significance. This is important even when the drift is small, because normalisation of the data inflates the impact of minor variations.

It has been shown that data compression can impact mean and standard deviation calculations (Thornhill, 2004) and can therefore interfere with many types of data-driven analyses. Kourti (2003) found that data acquisition and storage, if done improperly, may distort historical data and make them useless for MVA, and thus miss important phenomena.

Hodouin et al. (1993) experimented with various approaches for applying MVA to hourly averages from mineral processing data, including the use of mass balance filters to enhance data quality and the creation of new variables. However, the authors state that these data quality improvements tended to be destroyed by the MVA modelling process, although no explanation was given as to how this occurs. The authors recommended using multiple-input-multiple-output (MIMO) when the Y's are correlated with one another.

Zamprogna et al. (2002) developed a soft-sensor for a batch distillation column, using PLS as an alternative to first-principle modelling. They emphasise the importance of selecting the most appropriate model input variables, and correctly addressing lagged measurements. When performing MVA, time lags must be taken into account beforehand. MVA is not a time-series technique *per se*, and treats all observations as discrete events regardless of how far apart they are in real time. The use of moving averages can counter this problem (Eriksson et al., 2001). Nobleza et al. (1990) describe several time series analysis techniques using examples taken from the pulp and paper sector. Two of these, power spectrum and cross-correlation, could be used in parallel with MVA to extract useful insights about the production data.

The final challenge is that MVA results are difficult to interpret. In all cases, interpretations of the MVA results are based on an understanding of the process fundamentals, since the actual outputs from the MVA software are purely statistical (Saltin and Strand, 1995). The use of MVA for studying TMP process data is thus a task appropriate for chemical engineers.

CHAPTER 3.0 OVERALL METHODOLOGICAL APPROACH

3.1. Gaps in the Body of Knowledge

The various publications on industrial MVA applications, listed in Appendix I, share in common that they provide few if any details on how the MVA analyses were actually done. Often the underlying theory was described, but not the critical methodological decisions regarding how the different variables were selected for inclusion in the study, what limits were placed on the data used, or whether there was any data pre-treatment such as filtering, trimming or data reconciliation. Other gaps were methods for dealing with major data outliers, periods of start-up and shut-down, instrument drift, and noise. Determining a detailed methodology for applying MVA to time-series data from TMP newsprint mills is a useful and original contribution to the literature.

The question of temporal and spatial resolution is another gap in the current literature. There does not appear to be a consensus on the appropriate timescale to be used for applying MVA to TMP operations. Few of the papers give any justification for the timescale used, which can range from a few seconds to monthly averages. Also, it is not always clear exactly what parts of the mill were physically included in the PCA/PLS models.

The papers did not all find the same results from the perspective of linkage with engineering science. For instance, in one study paper machine variables were found to be the most important, while in another, chip properties were most important. This was probably due to the tendency of MVA to zero in on those variables which were actually included in the analysis, or which were measured better or more frequently, a major obstacle to obtaining accurate results.

Much fundamental work has been done over the past forty or more years to describe the physics of cellulose, fibrils, wood fibres and paper. However, connecting the underlying physics with the macroscopic properties of paper is difficult, due to its high degree of hydrogen bonding and extreme sensitivity to moisture and temperature. Equally difficult is relating upstream conditions to final product quality. Nevertheless, there is a solid basis in the literature upon which to erect scientifically meaningful interpretations of MVA correlations between TMP pulp freeness, fibre length and fines content and final paper strength, porosity and linting.

3.2. Case Study: TMP Newsprint Mill

The case study used for this project was a TMP newsprint mill in Eastern Canada which experiences short- and long-term variations in final paper quality. The goal was to infer the correlations and trends inherent to the mill operation using MVA, in order to determine which upstream parameters were most likely linked to these quality variations.

The main characteristics of the case study mill are provided in Appendix II, including several flowsheets and tables showing key process variables as well as time lags for the mainline pulp. These time lags are idealised, and assume plug flow which is not the case in this type of mill. The mill has a high-speed data historian into which virtually all process and operating data are continuously fed; there are over six thousand data 'tags', each representing an instrument or measurement point. Most of the process data from the mill are stored in compressed form.

The mill is equipped with ten Sunds Defibrator RGP-70-CD conical refiners, which have both flat and conical refining zones. The plate gaps are controlled independently; the plates in the conical part of the refiner are fixed, but the distance between these is adjusted by the displacement of the rotor. There is no advanced process control on these refiners, and all key operating decisions are made by the operators. Some operating variables at the refiners are measured every second, the data historian's lowest time increment, but pulp quality is only measured every few hours. Appendix III contains a chart of typical operator control actions, based on discussions at the mill, along with some relevant excerpts from the mill's Operator Manual.

The mill has two paper machines: Number 4, a Dynaformer top-wire unit on a Dominion Engineering Foudrinier; and Number 5, a Valmet-Dominion Sym-Former. The nominal production capacities are 150 000 t/a and 195 000 t/a respectively. Both machines are relatively new, and make 42-g, 45-g and 48.8-g newsprint. Paper machine operating variables are updated every second; some paper quality parameters are measured on-line in a continuous fashion, but those of interest to the project are measured off-line at the end of every reel.

Discussions with mill personnel revealed that variability in final paper quality was a key concern, notably for strength, porosity and linting, about which they have received customer complaints. It is not enough for the mill to attain quality targets; variations must be kept in check to avoid problems when the eventual customers use the newsprint in their printing lines. Mill personnel stated that there was a clear correlation between mill paper breaks and customer paper breaks.

A major challenge in the case study mill was the constant starting and stopping of the TMP lines, due to over-capacity relative to the papermaking section. When less pulp is needed, one of the four refining lines is temporarily shut down; about 70% of the time the mill is operating with three or fewer refining lines. Automatic shutdowns triggered by excessive motor load, known as feedguard events, represent another cause of production disruption. All four lines are operated the same way.

Overall, the mill has a number of data quality limitations, including a lack of measurements for some key parameters, and infrequent measurements for others. As such, it provides a good example of a situation where the data quality is poses serious challenges.

While the mill is very cooperative in allowing us access to their facility and information, they were not interested in performing 'bump' tests or any other kind of experiment, or changing the parameters of the data historian. This study was therefore entirely limited to historical operating data, nonetheless an important source of insight available to the modern-day process engineer.

3.3. Materials and Methods

The software used in this project was Simca-P, version 10, which was designed especially for chemical engineers by the Swedish supplier Umetrics. Data were obtained from the data historian at the mill site, which uses using PI software from Osisoft Inc. A partial list of the data tags used in this project appears in Appendix IV, along with their locations on the mill's P&ID diagrams. All data pre-treatment was done in EXCEL prior to importing into the MVA software. Some additional statistical tests were performed using the internal software developed by PAPRICAN.

The key fibre property measurements at the mill are shown in Table 3.1. Note that shives are not measured by the Pulp Expert unit at this mill, and that laboratory shive measurements are very infrequent (one grab sample per day).

The shortest time increment used at the mill in question is one second, which may be considered the lower limit. The server has been on line for several years, so one year could be considered the upper limit. It is possible to select virtually any time scale in between for analysing data for diagnostic purposes. In the refining section of the mill, there are several frequencies which guided the choices:

- Instantaneous pulp quality readings for Line 1 are taken every 60-120 minutes, on average.
- Off-line, instantaneous paper quality testing is done on each reel, roughly every 45 minutes.
- The residence time of the latency chest is approximately 45 minutes.
- The mill operates on three daily shifts of eight hours.
- The average mainline residence time for the entire mill (once-through fibre) is approximately 6.5 hours.

Three time scales were therefore selected:

- 1 hour, which roughly corresponds to the pulp sampling frequency, the paper sampling frequency, and the residence time of the latency chest.
- 8 hours, corresponding to one workshift, and is the same order of magnitude as the once-through residence time of the entire mill.
- 24 hours, corresponding to one day, an obvious option used by many previous authors.

Table 3-1: Fibre Property Measurements at Case Study Mill

Measurement Location	Instrument	Parameters	Principle of Operation	Frequency of Measurement	Nature of Sampling	Calibration Routine
Outlet of Latency Chest	PulpExpert EXP sampler/analyser	Consistency (%) Freeness (mL) Brightness (%) Fibre Size Distribution (mm or %)	Gravimetric measurements; CSF freeness test; digital imaging	60-120 min	Grab samples taken over 30 seconds; average of three trials	Maintenance and cleaning: 1x/d. Inspection and calibration if required: 1x/wk Complete overhaul: 1x/mo.
End of Paper Machine 4	Measurex 2200-2 on-line scanner	Basis weight (g/m^2) Dry weight (g/m^2) Moisture content (%) Thickness (μm) Colour (a*, b*, brightness)	Mobile scanner with digital imaging in visible and infrared range	Continuous	Zig-zag pattern (~60 s)	Verification against standards: 1x/d. Complete inspection: 1x/mo.
End of Paper Machine 5	Measurex 2002 on-line scanner	Basis weight (g/m^2) Dry weight (g/m^2) Moisture content (%) Thickness (μm) Colour (a*, b*, brightness)	Mobile scanner with digital imaging in visible and infrared range	Continuous	Zig-zag pattern (~60 s)	Verification against standards: 1x/d. Complete inspection: 1x/mo.
Off-Line Paper Quality	Lorentzen & Wettre Autoline 200	Thickness (μm) Upper Finish (μm) Lower Finish (μm) Porosity (mL/min) TSI MD (kNm/g) TSI CD (kNm/g) TSI MD/CD TSO Angle (deg) Bursting strength (kPa) Basis weight (g/m^2) Tear MD (mN) Tear CD (mN) Break MD (kN/m) Break CD (kN/m) TEA MD (J/m^2) TEA CD (J/m^2) Stretch MD (%) Stretch CD (%)	Automatic paper-testing unit in an enclosed laboratory	45 min	12 tests across full paper width; one 30-cm strip per reel	Inspection: 1x/wk. Internal calibration: 1x/mo. External calibration: 1x/3mos
		Linting	Black adhesive patch examined for fine surface particles	One test per 1000 m of paper	Introduced in the summer of 2004.	

3.4. Criteria for Evaluating Different MVA Models

Both quantitative and qualitative criteria were used to evaluate the different MVA models that were created, as shown in Table 3.2, to maximise the likelihood of discerning differences between the models that were created.

Table 3-2: Criteria for Evaluating MVA Models

Criterion	**Parameter Used**	**Type of Output**
GOODNESS OF FIT	Q^2 for overall model	Quantitative
	Q^2 for each Y	Quantitative
	Predicted vs. Observed for each Y	Scatter plot
COMPLEXITY OF MODEL	Number of components required for a given Q^2	Quantitative
REALISM OF MODEL	Relative prominence of X variables	Ranking
	Interpretability of components with regard to process fundamentals	Qualitative

Note that Q^2 is a measure of goodness of fit analogous to R^2, but it is specific to predictive power; it is the percentage of overall measured variance that is attributable to the model's predicted values. It is derived by separating the dataset into several segments, some used to create the components, and others for testing the model. Unlike R^2, which always increases when a model is made more complex, Q^2 tends to plateau and then diminish sharply when there is over-fitting.

On the physical/chemical side, the models were evaluated with respect to whether they were logically interpretable, i.e., interpretation of various PCA/PLS components, coherence of variables that are correlated/anti-correlated, and so forth.

Over the course of the project, key results were presented to mill personnel for "real-world" validation, an invaluable aid in ensuring that the findings had a solid foundation and were not mere statistical manipulations. In fact, the mill's Process Director appears as co-author on some of our publications.

CHAPTER 4.0 PUBLICATION EXECUTIVE SUMMARY

4.1. Presentation of Publications

The following publications are presented as appendices to this thesis:

- INTERNATIONAL PEER-REVIEWED PUBLICATION (Appendix V): Harrison R., R. Leroux, P.R. Stuart (2004). Multivariate Analysis of Refiner Operating Data From a Thermo-Mechanical Pulp Newsprint Mill. Pulp & Paper Canada, 105:4, pp. 24-27.
- PEER-REVIEWED CONFERENCE PAPER (Appendix VI): Harrison, R., P.R. Stuart (2003). Processing of Thermo-Mechanical Pulping Data to Enhance PCA and PLS. Proceedings from ESCAPE-13 Conference, Lappeenranta, Finland. Printed in Computer-Aided Chemical Engineering, vol. 14, 1025-1030.
- PEER-REVIEWED CONFERENCE PAPER (Appendix VII): Harrison, R.P., R. Leroux, P.R. Stuart (2005). Representing TMP Process Fundamentals by Creating Non-Linear Terms in Multivariate Analysis. 91st Annual PAPTAC Meeting Preprints, D563-D568.
- INTERNATIONAL PEER-REVIEWED PUBLICATION (Appendix VIII): Harrison R., P.R. Stuart (2006). Techniques for Pre-Treating TMP Process Data for Multivariate Analysis. Tappi Journal, 5(8), pp. 17-23.
- INTERNATIONAL PEER-REVIEWED PUBLICATION (Appendix IX): Harrison R., A.A. Roche, P.R. Stuart (2006). Impact of TMP Refining Line Interruptions and Reject Refiner Operations on Pulp and Paper Variability. Accepted for publication by Tappi Journal on January 15, 2007.
- INTERNATIONAL PEER-REVIEWED PUBLICATION (Appendix X): Harrison R., P.R. Stuart (2006). Spatial and Temporal Resolution in the Data-Driven Process Modeling of an Integrated Newsprint Mill. In review. Received by Journal of Chemical Product and Process Modeling on December 7, 2006.
- INTERNATIONAL PEER-REVIEWED PUBLICATION (Appendix XI): Harrison R., P.R. Stuart (2006). Extracting Process Relationships from Historical Databases of Continuous Industrial Processes. In review. Received by Industrial & Engineering Chemistry Research Journal on December 18, 2006.

The links between these publications are described below, along with their positions within the overall methodological approach presented in Chapter 3.

4.2. Links between Publications

The first peer-reviewed article (Appendix V), which appeared in the April 2004 issue of Pulp and Paper Canada, was originally presented at the 2003 PAPTAC meeting in Montreal. The objectives were to explore the limitations of MVA, and to identify which TMP variables were most useful for modeling pulp quality. PCA and PLS were performed on daily averages over 34 consecutive months, using different combinations of variables upstream and downstream from the primary and secondary refiners. Pulp throughput dominated the results even within a relatively narrow range of normal production rates. This paper corresponded to the initiation of Objectives #1 and #5 listed in Section 1.2, and paved the way for the two conference papers that followed.

The conference paper in Appendix VI was presented at the European Symposium of Computer-Aided Process Engineering (ESCAPE-13) conference in Finland. This was a preliminary examination of the differences, if any, obtained in multivariate analysis results using different timescales and averaging methods on compressed historical data. Overall, it was found that medians gave slightly better results than averages (unfortunately the PI system used at the case study mill cannot calculate medians). Low production points tended to dominate other variables. The optimal timescale depended on the intended application. Generally, the same X variables are prominent regardless of the timescale used, but the goodness of fit of the model was heavily influenced by the sampling frequency of key process parameters. This paper, plus the detailed examination of MVA challenges and limitations outlined in the Literature Review (Section 2.5 above) marked the completion of Objective #5.

The conference paper in Appendix VII, presented at the 91st Annual PAPTAC conference in Montreal, included an attempt to more accurately represent TMP fundamentals with a variety of new non-linear variables constructed from measured variables. These included blowline consistency derived from a mass/energy balance, steam pressure drop across the refiner, and hydraulic pressure delta. The inclusion of standard deviation, variance, logarithm and other non-linear operators was found to have little impact on the MVA models, at least for the parameters and time periods that were studied. This paper was a continuation of Objective #1. It also initiated certain elements of Objectives #2 and #4.

The second peer-reviewed paper (Appendix VIII) originally appeared as a Paprican University Report, and was subsequently published by Tappi Journal in August 2006. This study presented a straightforward method for selecting and pretreating TMP operating data, to improve statistical tracking of pulp quality variations. This paper focussed on pre-selecting and pre-treating the raw process data, including infrequently measured variables, to maximize the realism and usefulness of the PLS black-box models. Key methods explored were ways of selecting low-production periods for removal, techniques for identifying and eliminating major outliers using PCA outputs, and noise filtering. A major conclusion of this work was that the PLS models were significantly improved by pre-treating the data, with stringent removal of dubious periods of operation such as aberrant process behaviour, and an aggressive Exponentially Weighted Moving Average (EWMA) filtering of all Y and X variables. This approach, used in all subsequent work, marked the completion of Objective #2.

The third peer-reviewed paper (Appendix IX), also submitted to the TAPPI Journal, presents a straightforward method for combining individual TMP operations, including reject refining, into a single statistical model for explaining quality fluctuations in pulp and final newsprint. This article demonstrates the statistical correlations between TMP operations, pulp quality and final paper quality, by focusing on process fundamentals such as specific energy and refining intensity. Frequent interruptions in the four refining lines greatly affect the reject specific energy and other key parameters, many of which are not measured directly and must be calculated from other variables. Using Multivariate Analysis and other statistical tools, it was possible to link pulp quality back to TMP and rejects operations, taking into account the number of lines in operation, plate age and process lags. Furthermore, it was possible using MVA models to correlate roughly half of the variability in final paper quality with the refining operations. One conclusion of this work is that even better results would likely be obtained with more on-line measurements, notably for incoming chip quality and reject refining consistency. This paper marked the end of Objective #1.

The fourth peer-reviewed paper (Appendix X) is under review by the Journal of Chemical Product and Process Modeling. The study continues on previous work by comparing the use of different timescales and combinations of unit operations to determine which yield the best simulations. Because we are using real operating data, with no experimental design of any kind, it is possible that some of the correlations found could be attributable to mere coincidence. We therefore used time-series and other mathematical techniques to explore the validity of the models. This paper corresponds to Objectives #3 and #4.

The last paper, currently under review by Industrial & Engineering Chemistry Research Journal, elaborates an overall methodology for applying MVA to TMP historical operating data. It is the logical outcome of all six previous papers, and corresponds to the completion of Objective #6.

4.3. Synthesis

Pursuing this research project has involved collecting millions of datapoints and creating hundreds of statistical models. Throughout, the results have been the subject of detailed discussions between the student and the research supervisor, as well as with Mr. Alain Roche of PAPRICAN and Dr. Martin Fairbank of Abitibi-Consolidated. While it is impossible to present all these results here, the following text provides an overview of the progression of the project and its key findings.

The goal of this study was to use MVA to understand the correlations and trends that are inherent to Thermo-Mechanical Pulp (TMP) mill operation, in order to determine which upstream parameters are most likely linked to newsprint quality. The case study was a TMP newsprint mill in Eastern Canada, which experiences short- and long-term variations in final paper quality. As is the case with most MVA studies of existing operations, in the absence of a designed experiment all results were dependent on the natural variability pre-existing in the dataset.

Modern mills are faced with a new challenge, namely a glut of process data captured by millwide data historians. While theoretically a gold mine of information on the inner workings of the different unit operations, in practice it is often difficult to show trends and relationships connecting the different sections of the mill. Missing, sparse and/or poor measurements are partly to blame, but another equally important reason is the multivariate nature of the TMP mill itself and the difficult task of identifying and quantifying nonlinear relationships.

Studying one or two variables at a time is a fruitless task, because the operating parameters, pulp measurements and final paper quality are connected in such a way that the interactions between them are as important as the variables themselves. To be properly understood, the different variables in a TMP mill must be studied in combination. One method is the statistical technique known as Multivariate Analysis, or MVA. Like all so-called "black-box" methods, which rely only on inputs and outputs, it has the pitfall of blindly attributing correlations between variables without any regard whatsoever for the actual underlying process.

MVA works by reducing the dimensionality of large datasets, to make them more manageable and hopefully more understandable. The advent of modern computing power has made it possible to apply MVA to millions of data points, and it has been used in a variety of industrial sectors (Mason and Young, 2004) including pulp and paper (Strand et al., 2001; Lupien et al., 2004; Saltin and Strand, 1995; Nobleza, 1997, Browne et al., 2004).

The case study mill has four operating TMP refining lines, two paper machines, and over six thousand data collection points or 'tags', of which several hundred are directly relevant to the papermaking process. At the start of the project, the data historian had been operating for almost three years, with some process values logged every second. Thus, the choice of variables and time periods for the project was virtually infinite.

The choice of timescale was likewise basically infinite. Previous papers on TMP operation had used a variety of timescales, ranging from monthly averages to instantaneous readings (Lupien et al.., 2001; Saltin et al.., 1995; Shaw, 2001; Strand et al.., 2001). Theoretically, MVA models of the case study mill could be created using yearly averages, or second-by-second data, or any time increment in between.

The first order of business was to create some exploratory MVA models, using previously published examples as a guide. For the most part, data pre-treatment was done in EXCEL prior to downloading the data into the MVA software, SIMCA-P (version 10) from Umetrics AB. Starting with daily averages on a single TMP refining line, various initial models were created to compare:

- Large versus small number of variables
- Principal Component Analysis (PCA) versus Projection to Latent Surfaces (PLS)
- Summer versus winter
- High-production periods versus low-production periods

The quality variables used were pulp freeness and fibre length, measured by the on-line automated PulpExpert unit at the outflow of the latency chest. Both are known to play a critical role in final paper strength (Saltin and Strand, 1995; McDonald et al., 2001), the main newsprint characteristic of interest to the mill.

One of the benefits of MVA is that it differentiates very clearly between those variables which contributed much to the model, and those that contributed little. The results of the earliest models allowed us to hone in on certain TMP refiner variables that were closely associated with freeness and fibre length: throughput, specific energy and plate gap. At this stage, however, we only had a preliminary notion of how to model a TMP refiner with MVA, which would later be improved as other factors like data pre-processing were considered.

Wood chips, being the main raw material, received much attention early in the project. The mill has a maximum two-day chip pile inventory, such that there is little or no buffering of incoming chip variability, making the entire process highly susceptible to fluctuating chip quality. The mill operates on 100% wood chips, using a combination of black spruce and balsam fir. The mill has minimal chip inventory, and a variety of outside chip suppliers. Often the exact source and softwood species are unknown. Size, density, and humidity are measured in a lab using grab samples collected every 8 hours at the chip silo feed conveyor, which feeds all four TMP refiner lines. Size distribution is measured with a Gradex unit at the chip receiving lab; other parameters are measured manually in the laboratory.

PCA on the TMP feed conveyor data yielded a combined Q^2 of 20%. There was only one principal component, very strongly correlated with season:

- Higher in summer: chips longer than 5/8 in.
- Higher in winter: chips shorter than 3/8 in.; chip density; chip moisture.

These trends were already obvious from the raw data, and make sense physically. The interesting point is the lack of any other components, indicating no other statistically significant correlations between the chip properties. This may be partly due to the sparseness of the data, with few measured parameters and only three grab samples per day. Little or no information was available on the wood species, freshness of the wood, the age of the tree, chipper type or other factors which can impact on final pulp quality (Nobleza, 1997; Wood, 2001).

No significant correlation was found between the measured chip characteristics and the mainline pulp quality, other than the above-mentioned seasonal variations. These findings would indicate that the chip quality data are too sparse and limited to be useful for this kind of statistical analysis, and confirm the need for better measurement tools for incoming chips such as optical scanners (Smith and Derby, 2004). Note that several on-line woodchip monitors are under development in Canada, though none is yet commercially available (Ding et al., 2005; Bédard et al., 2003; Laperrière et al., 2004; Lanouette et al., 2003).

To better characterise the seasonal trend, latency chest pulp quality parameters were compared to the average monthly temperature from a nearby Environment Canada meteorological station. A time lag of 60 to 80 days was found, depending on the pulp parameter in question. For example, average fibre length, which varied from 1.2 mm to 1.5 mm throughout the year, was compared to ambient temperature in a cross-correlation plot. The highest coefficient, and hence greatest correlation, occured when temperature is shifted by about 80 days relative to the fibre length. This trend confirmed statements by mill personnel that the most typical "winter" operating conditions occur in March, and the most typical "summer" conditions are in August, a lag of about 60 days. This is thought to be due to the time from tree felling to chip use. Therefore, the time periods selected for the rest of the study were the months of March and August over two consecutive years, 2003 and 2004.

Before proceeding further, we had to select the definitive list of product quality variables for the study. Several dozen measurements are done routinely at the mill on the final newsprint. Some are continuous, but those of chief interest are measured only once per reel by an off-line automated Autoline unit. Based on conversations with mill personnel, internal discussions, review of the literature, and our own MVA modelling to that point, we selected the parameters listed in Table 4.1.

Table 4-1: Dependent (Y) variables used to generate PLS models.

Variable	**Unit**	**Time between measurements**
Paper Properties (Autoline)		
Tear MD (index)	$mN/(g/m^2)$	45 min
Tear CD (index)	$mN/(g/m^2)$	45 min
Bursting strength (index)	$kPa/(g/m^2)$	45 min
TSI MD	kNm/g	45 min
TSI CD	kNm/g	45 min
Permeability to air (indicative of porosity)	mL/min	45 min
Linting (black adhesive patch examined for fine surface particles) – Top	%	45 min
Linting – Bottom	%	45 min
Pulp Properties (PulpExpert)		
Canadian Standard Freeness	mL	60-120 min
Average fibre length (length-weighted)	mm	60-120 min
Fines content, defined as small enough to pass through 200 mesh screen (76 μm)	% (mass)	60-120 min

Pulp samples at the mill are automatically analysed roughly every 60-120 minutes, as shown in Table 4.1. The sampling itself only lasts some 30 seconds, so these are grab samples and not composite samples. Along with the inevitable measurement error and calibration issues, this tends to create much variability from one reading to the next.

Note that, in addition to freeness and fibre length, fines content was added to the list of pulp characteristics, largely based on its pertinence to linting. Fines content has also been reported to be critical to paper strength, since fine particles can enhance inter-fibre bonding when the fibres are insufficiently developed (Law, 2005).

Even though they each receive exactly the same pulp feed, the two paper machines are of slightly different design and are operated independently. We therefore elected to do separate models for each machine. Likewise, past experience had shown that it is best to do separate MIMO models for each group of related Y's: paper strength (5 variables), permeability (1 variable), and linting (2 variables).

Pulp refining is a highly complex process using a biological feed material, so fundamental models to date have been semi-empirical in nature (McDonald et al., 2004). Excessive refining intensity can damage fibres, even when specific energy and freeness appear normal, leading to reduced fibre length and tear strength (McDonald et al., 2004). When the refining intensity is high, the desired freeness is achieved through fibre cutting instead of fibre development, resulting in the type of gain reversion described by Roche *et al.* (1996). In a conical refiner it is difficult to model refining intensity directly, as no equations analogous to the Miles and May model have been published for this type of refiner. The goal was therefore to model refining intensity indirectly, if possible, using existing measured variables.

Refining intensity is defined as the specific energy delivered per refiner bar impact. For a given plate configuration and disc rotation speed, it is largely a function of refining consistency (Roche et al., 1996). This is an inverse relationship, since greater consistency means a longer residence time between the refiner plates and hence more bar impacts for a given specific energy. Refining intensity in the secondary stage has been shown to have a significant impact on softwood pulp quality (Miles, 2003; Lama et al., 2004), so it is generally desirable to have lower refining intensity in the second stage to avoid excessive fibre cutting.

At the case study mill, the individual plate ages are continuously logged in the data historian, and so were readily available for use in the models. During their lifetime, the bars on the plate surface are gradually worn down, affecting the process dynamics. Less energy is required with an older plate, but the refining intensity is higher because the plate gap is smaller, resulting in more damaged fibres

(Croteau, 1993). Normally, therefore, one would expect shorter fibres and more fines associated with older plates.

Based internal discussion, review of the literature, and our own MVA modelling we selected the TMP refining parameters listed in Table 4.2.

Table 4-2: X variables used to generate PLS models

Variable	**Unit**	**Time between measurements**
Production rate (proportional to feed screw rotational speed)	t/d	1 second
Number of TMP lines in operation	–	1 second
1° & 2° specific refining energy	kWh/t	1 second
1° & 2° blowline consistency (calculated with simple mass/energy balance)	% solids	1 second
1° & 2° plate age	H	1 second
Standard deviation of motor loads (1° & 2°)	MW	1 second
Reject refining specific energy	kWh/t	1 second
Reject plate age	h	1 second

Turning to the question of process dynamics, the first point to consider is that final paper quality is tested using small strips at the end of each reel. This is unavoidable, because newsprint is sold in long continuous sheets, which would be destroyed by intermittent cutting. This means, by definition, that any MVA models constructed using these data will be limited to long-term fluctuations in paper quality, and totally blind to shorter-term fluctuations such as would occur within a single reel.

As it happens, newsprint variations tend to be long term, due to the buffering effect of control loops. However, the question remains whether even these slower trends are adequately represented by the data actually collected. Following the technique recommended by Croteau et al. (1993), we studied the power spectra of all the paper characteristics of interest, using one-hour averages. We found that three-quarters of the variability in tear strength occurred at a frequency below 0.1 cycles per hour, i.e., at a time constant above 10 hours. Similar plots were found for all the paper parameters under study. Over 95% of the variability was below 0.4 cycles per hour, i.e., longer than 2.5 hours, probably due to control loops at the paper machine. These control loops maintain constant paper weight, thickness and moisture content, and reduce short-term variations in paper strength. These results would suggest that the slower trends in final paper quality are indeed adequately represented, and that this sampling frequency is sufficient for our purposes.

Theoretically, it is possible to create MVA models using data extracted at 1-second increments. This would have required some form of interpolation for intermittent measurements, such as the 2-hour pulp quality grab samples, an extremely gross approximation. The use of the previous recorded value is also of no use in this case, since MVA looks for variables which tend to move at the same time, and would be "fooled" into thinking that a major process shift is occurring every two hours or so. The same argument applies, to a lesser extent, to shorter averaging time scales such as 1 minute or 10 minutes. To perform MVA at such a timescale, much more frequent pulp sampling would be required. Residence times in the different unit operations would also have to be known to an equivalent precision, to ensure that all time lags and time constants are accounted for during the data pre-processing.

To avoid such extreme interpolation between real measurements, we selected three timescales for the study. The shortest, a 1-h average, was selected because it is in the same order-of-magnitude as the pulp sampling period (60-120 min) and the paper sampling period (45 min). It is also close to the 45-min retention time in the all-important latency chests, the large holding tanks at the end of each refining line where refined fibers are given the time to disentangle. The second timescale, an 8-h average, was chosen to represent a typical workshift. It also corresponds roughly to the overall once-through retention time of the entire TMP mill (6-7 h). The third timescale, a 24-h average, simply represents one day of production and has been used by other authors (Ortiz-Cordoba et al.., 2006; Lupien et al.., 2001; Saltin et al.., 1995). The 8-hour and 24-hour means were calculated from our own 1-h database, with production stoppages and other process upsets already removed, rather than directly from the data historian where such outliers would have skewed the values.

When applying MVA to raw data from an industrial facility such as a pulp and paper mill, it is critical to select and pre-treat the data adequately. MVA is a black-box statistical technique, entirely data-driven. As a least-squares method it is inevitably drawn to overemphasising extreme values such as large process fluctuations, at the expense of normal operating conditions.

Early in the project, some initial data pre-processing was carried out to compare various options, including averaging methods. For instance, medians were found to give better MVA results than means, possibly because they are less influenced by extreme values. Unfortunately, though, the data retrieval system at the case study mill did not offer this option, so the arithmetic mean ('average') was used for the remainder of the project.

Some of the specific energy values encountered in the data historian were nonsensically high, sometimes by two orders of magnitude. This appears to have been caused by automated calculations using a near-zero values in the denominator. For the purposes of this project, therefore, all specific energies were calculated directly from the values for motor load and throughput.

Freeness is often linearised by taking its logarithm, as was done in a previous MVA paper (Browne et al., 2004). To determine whether linearisation of freeness data was appropriate for the TMP operation being studied, MVA models using both the logarithm and the original values were compared. Virtually no difference was found. The most likely explanation is that within our dataset the freeness only varied between 200 and 250 mL, which is too small a range for the non-linearity to show itself. We therefore used the original freeness values.

A major challenge in this study was the regular starting and stopping of the TMP lines, due to built-in over-capacity relative to the papermaking section. Direct use of the raw data would have yielded meaningless MVA results, since the algorithm would attribute most of the correlation to the start/stop phenomenon, and not to actual changes in the process during normal operation. The main cause of production disruptions at the case study mill is built-in overcapacity relative to the paper machines. When less pulp is needed, one of the four refining lines is temporarily shut down, such that the mill is operating with only three or fewer refiner lines about 70% of the time. All four lines are subjected to these shutdowns.

To counter this and other problems, we subjected the raw data to the step-by-step approach outlined in Figure 4.1.

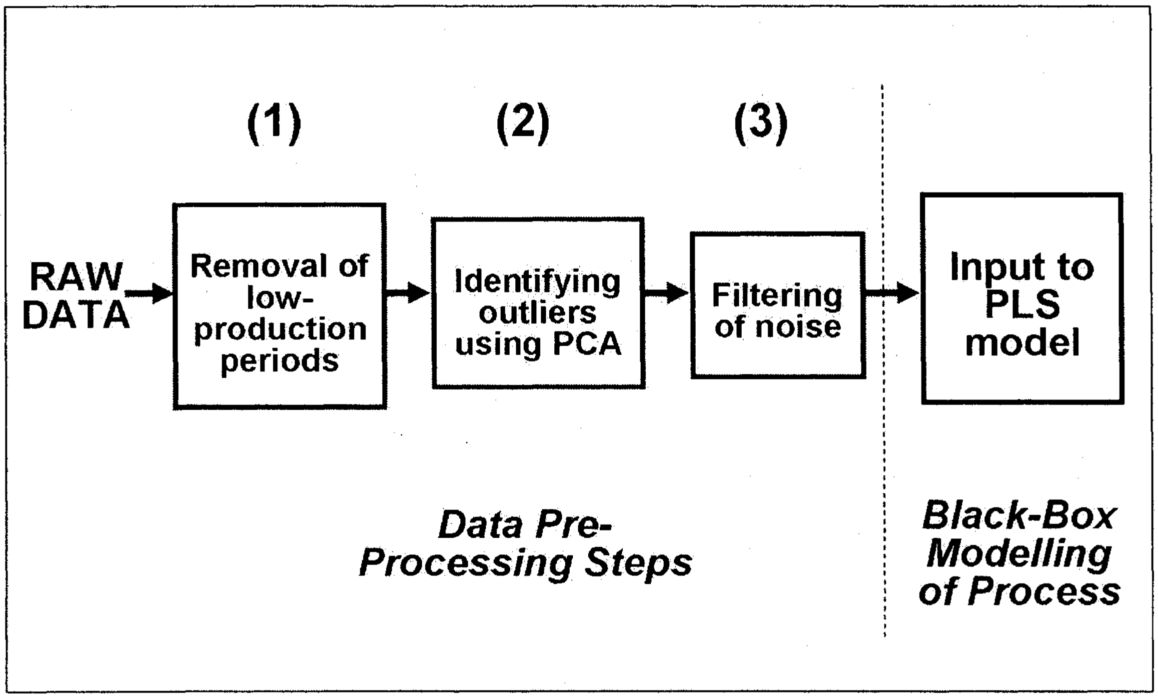

Figure 4-1: Overall data pretreatment strategy applied to TMP historical data.

Using August 2003 as a reference time period, two options for dealing with low-production periods were compared. As shown in Figure 4.2, removing periods where the mean production was below the threshold was found to be inadequate. The mean in this case disguised short periods of low production.

'Minimum' production, as opposed to mean production, refers to the smallest value recorded on a second-by-second basis within any one-hour period. A threshold of 200 t/d was selected because the TMP operators never intentionally operate the refiners below this rate. Using the more stringent *minimum* test resulted in a much clearer picture of the overall periods suitable for further study (Figure 4.2, bottom graph).

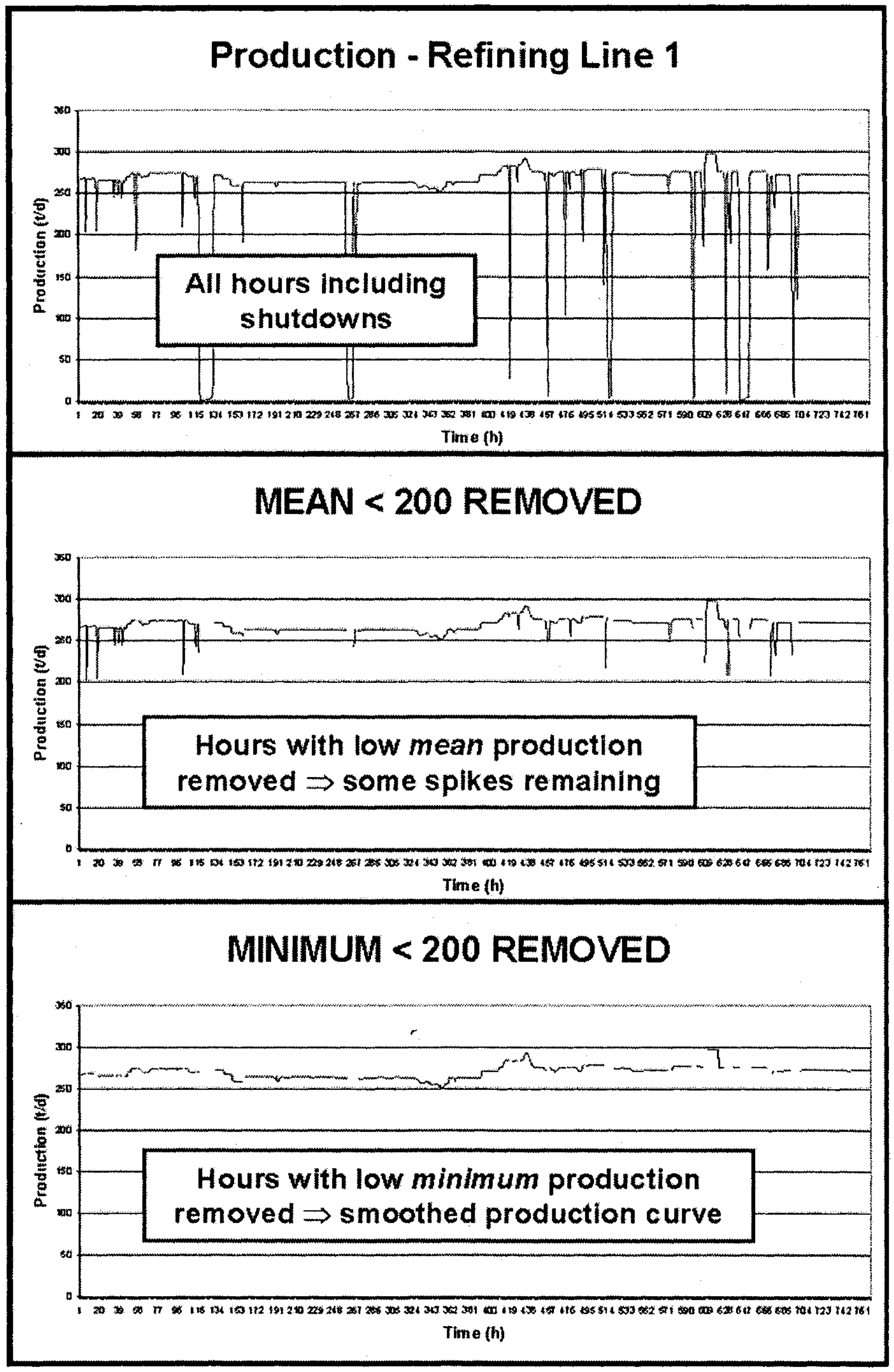

Figure 4-2: Hourly production rates for refining line 1 (expressed as metric tons per day) for the month of August 2003.

To complete the comparison, PLS models were generated using the various datasets listed in Table 4.3. The Q^2 shown is a combined metric for all three dependent (Y) variables, namely latency chest freeness, fibre length and fines content; the results obtained would be different if each dependent variable had been modeled separately.

PCA differs from PLS in that it treats all variables the same, rather than dividing them into X's and Y's. Two PCA are particularly useful for identifying outliers, 'score' plots which show how each observation fits within the model space relative to all the others, and 'Distance-to-Model' plots which show how far each data point had to be projected to be included in the model. To eliminate subjectivity in interpreting these plots, only points falling outside Hotelling's T^2 (95-percentile) were considered outliers. The Simca-P software shows this threshold as an ellipse on the score plot, and as a horizontal line on the distance-to-model plot.

Table 4-3: Results for PLS models generated from refining line data, with different hours excluded

Dataset	**Overall Q^2**	**# of Comp.[2]**	**Comments**
All hours	22%	5	Dominated by start-up & shutdown
- *minus outliers*[1]	41%	5	Dominated by start-up & shutdown
Mean < 200 removed	39%	5	Start-up & shutdown still strongly evident
- *minus outliers*	39%	4	Start-up & shutdown still strongly evident
Min. < 200 removed	40%	4	Minimal evidence of start-up & shutdown
- *minus outliers*	41%	4	Option retained

1 Rows marked "- *minus outliers*" indicate that both types of PCA outliers were removed.

2 The column identified as "# of Comp." refers to the number of significant components found, based on the best cumulative Q^2.

Thus, the PLS results for August 2003 confirmed that the best option was to remove *a priori* the periods with minimum production below the threshold, and then take out the outliers using PCA. However, the differences between some of the Q^2 values are slight, and in the case of "Mean < 200 removed" there was no appreciable difference when the outliers were removed. It was therefore necessary to investigate further by examining the actual nature of the datapoints that were removed in each case.

Using the MVA contribution plots for these points, it was possible to determine which variables had caused them to break with the overall correlational structure. The few dozen distance-to-model outliers were mainly due to changes in pulp parameters that were uncorrelated with the other variables, or to fluctuations in steam pressure drop across the refiner, possibly indicating temporary obstructions to counter-current steam flow between the refiner plates. Overall, this small number of outliers appeared to represent unusual operating conditions.

To test the effectiveness of MVA for detecting known outliers, a PCA model was created using all variables and datapoints, including low-production periods, for each of the four months under study. The data points identified using Hotelling's T^2 ellipse (95-percentile) often corresponded to the periods of low production, but not always. More importantly, some low-production periods were not detected at all.

Exponentially Weighted Moving Average (EWMA) is the most widely used form of filtering in the chemical process industries. Figure 4.3 shows plots of the original primary and secondary motor loads for August 2003, overlaid by the filtered signals for two different values of alpha in EWMA. Alpha is the weighting, between zero and one, given to the previous value in the sequence.

The lower value of 0.5 was the point at which smoothing started to become visibly apparent on the plots. The upper value of 0.8 was chosen because it yielded the smoothed curve that fit the original data the best, admittedly a somewhat subjective evaluation. At alpha values above 0.9, the curves became visibly over-fit. Note that with an extreme alpha (> 0.99), all signals begin to resemble a straight line.

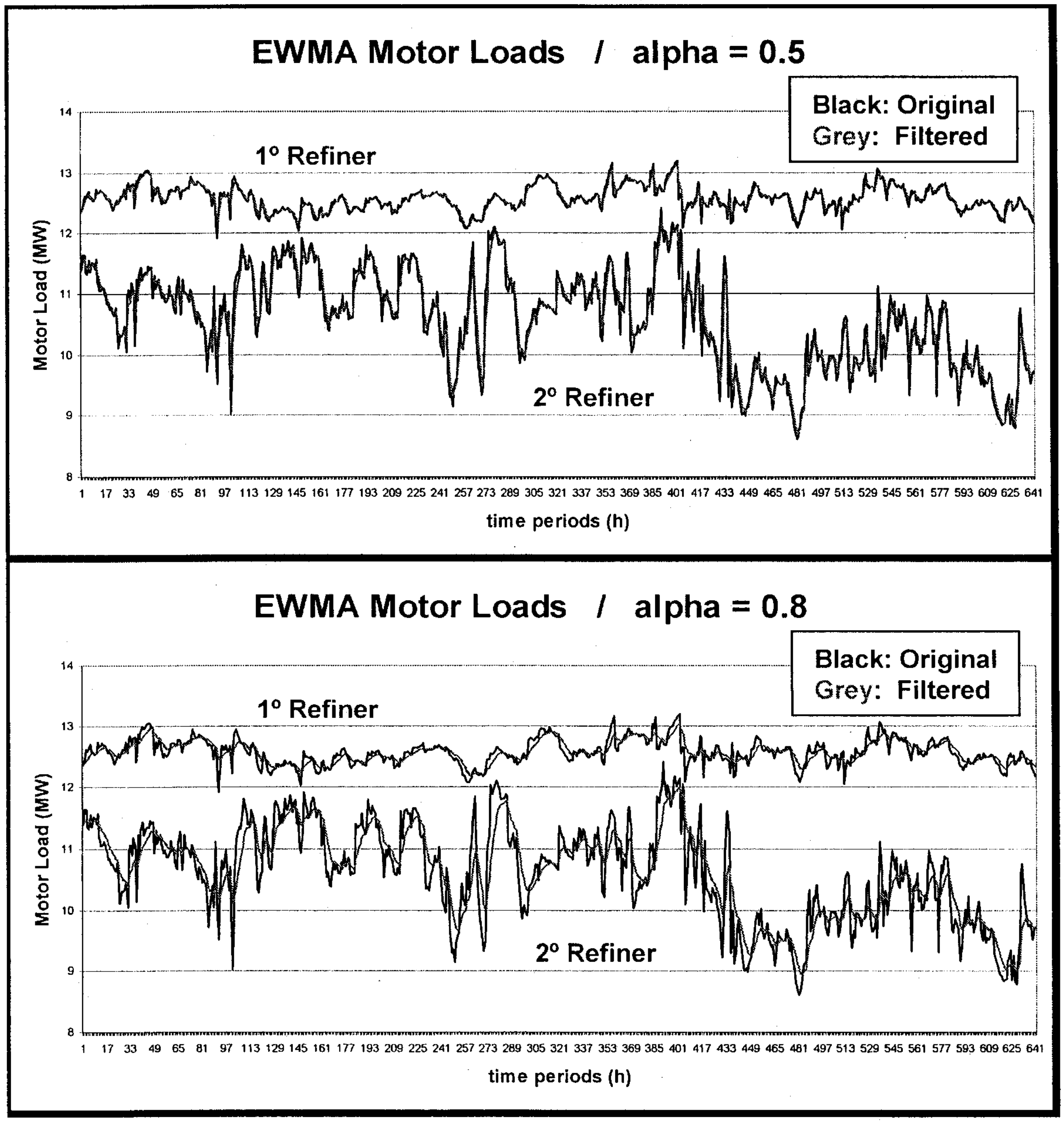

Figure 4-3: Filtered vs. original motor load signals for August 2003, showing smoothing effect of exponentially weighted moving average at different alpha values.

The results of the various PLS models for August 2003 are shown in Table 4.4, along with the combined Q^2 value for the three dependent variables (freeness, fibre length and fines). In all cases, components numbered 5 and above contributed little or no incremental gain to the overall goodness of fit, and may therefore represent random noise in the data. The improvement in goodness of fit when EWMA is applied is striking, with a jump in Q^2 from 41% to 61% simply by using an alpha of 0.8.

Table 4-4: Comparison of PLS results for different data filtering methods

Filtering option	**Overall Q^2**	**# of Comp.**[1]
No filtering	40.63%	4
Trim / winsorize	40.56%	4
EWMA, $\alpha = 0.5$	50.13%	3
EWMA, $\alpha = 0.8$	60.75%	2

[1] The column titled "# of Comp." indicates the number of components required to achieve an overall cumulative Q^2 equivalent to that of the "No filtering" case.

Trimming and winsorizing are automated features of the Simca-P software (Umetrics, 2002), and serve to remove extreme values. The trimming/winsorizing step entailed the removal of the top and bottom 1% of values for each individual variable, and their replacement with the value at the cut-off point. Since these features are routinely employed by MVA users, they were included in this study for the sake of comparison. This option had little impact on the results. This was not surprising, since intuitively this method does not seem suited to time series data, where the most extreme values might be due to process shifts and not aberrant measurements.

In order to combine the four TMP refining lines and two paper machines into a coherent MVA model, it was necessary to consider the quality of the data for each section. The final variables, with all production lines combined together, are shown in Figure 4.4.

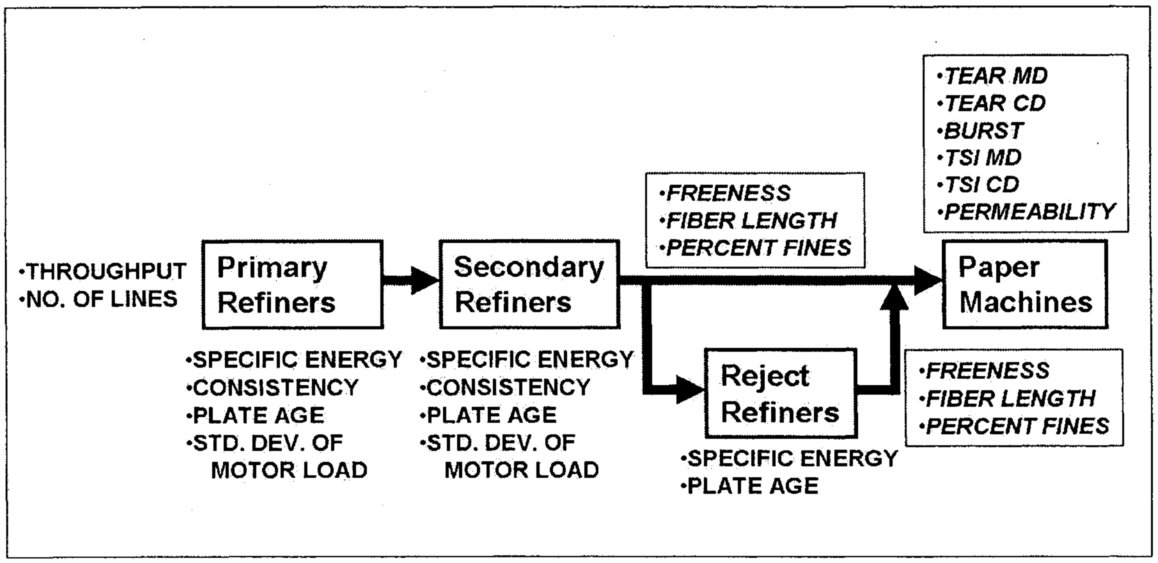

Figure 4-4: Structure of PLS model showing X and Y variables.

As shown in Table 4.5, the data for pulp quality was relatively poor. In contrast to the pulp, for paper the number of variables tested automatically is much higher, and there is a certain degree of redundancy among the numerous strength tests. However, measurements are still relatively infrequent. Tests are performed on a 30-cm wide strip at the end of each reel, again a small grab sample, corresponding to a period of roughly every 45 minutes. For the purposes of this study, the following paper parameters were used: tear strength, burst strength, TSI and permeability (porosity). These were selected based on preoccupations at the case study mill, and known relationships with the parameters tested in the pulp.

Table 4-5: Rich vs. Poor Data Sources at Case Study Mill

Data Source	Frequency of Measurement	Number of Variables	Richness of Data
Wood chip quality	Grab sample every 8 h	A few physical characteristics	Very poor
TMP mainline operation	Once per second	Large number of energy, pressure and flowrate measurements	Rich
Reject refiner operation	Once per second	Some key variables missing; must be calculated	Rich
Pulp quality – latency chest	Grab sample every 60-120 min	Limited to freeness, fibre length and fines	Poor

Data Source	Frequency of Measurement	Number of Variables	Richness of Data
Pulp quality – stock prep.	Grab sample every 60-120 min	Limited to freeness, fibre length and fines	Poor
Final paper quality	Grab sample every 45 min	Many variables with much redundancy, esp. for paper strength	Intermediate

Sparser still are measurements on the incoming chips, tiny grab samples which are taken from the main conveyor belt only every eight hours. Furthermore, the tests performed on the chips are limited to density and moisture measurements, a rough size distribution, and rot content. Apart from very long term trends, such as season-to-season, these chip data were far too limited to be useful for predicting final paper quality.

In stark contrast, the mainline refining and reject sections are rich in frequent, plentiful data. The refiners and ancillary equipment are highly instrumented, with many operating parameters measured continuously. Fast variables, such as motor load, are logged in the data historian once per second, providing a very large amount of process information. However, these data present some important challenges:

- Certain critical operating parameters go unmeasured, e.g., refining consistency.
- Variables are not in a form corresponding to known process fundamentals.
- Measurements are subject to instrument drift and calibration problems.
- Frequent start/stop of refiners.
- Gradual effect of equipment wear, such as plate age.
- Presence of process lags.

Some of these challenges, like instrument drift and equipment wear, are true of any TMP mill. Others, like lack of refining consistency measurement, are specific to the case study mill.

Despite these challenges, it should be possible to exploit the richness of the refining data to model pulp and newsprint quality. Because MVA is a linear technique, however, it is necessary to modify the variables to correspond better to the underlying process. TMP refiner operation is dominated by two non-linear terms: specific energy and refining intensity. Both must be calculated from other variables.

Specific energy is the central parameter of refiner operation. It must be high enough to ensure fibre separation and defibrillation, but low enough to avoid excessive fibre cutting which can adversely impact the strength of the final paper (Roche et al., 1996). Specific energy is not controlled directly, but rather indirectly via the manipulated variables of throughput, dilution flow and plate gap. It is relatively easy to calculate, since motor load is very accurately measured. Production rate is known from the volumetric feedrate, although the latter is susceptible to fluctuations in chip density.

Refining intensity is much more difficult to measure in an industrial refiner. At the case study mill, refining consistency is not measured directly in real time, but for Line 1 an on-line calculation is made available to operators based on a simple mass/energy balance. By comparing the equation in the DCS logbook to real production data, it was possible to deduce the coefficients and extend this calculation to the other three lines.

A very important, and sometimes overlooked, part of any TMP mill is rejects refining. Because the case study mill experiences frequent starts and stops on the four main refining lines, the throughput at the presses, and ultimately the reject refiners, is continually changing. Partly to compensate for this, the operators tend to increase the reject rate from roughly 30% to 40% after a line stoppage, meaning that the fibre length distribution of the pulp entering the reject refiners varies over time. These adjustments are made manually and not automatically, so there tends to be a lag of several hours. Combined with occasional stoppages of the reject refiners themselves, this situation results in a highly variable and poorly controlled reject refining.

Unfortunately, the measurements at the reject refiners are insufficient to calculate the consistency, which could serve as an indicator of reject refining intensity. However, it is possible to calculate the specific energy at the reject refiners, by adding the motor loads of the two reject refiners (they operate in parallel) and dividing by the throughput. The latter was estimated by simply multiplying the reject rate (%) by the total production of the four main lines (t/d). The specific reject refining energy that was thus calculated showed a very large variability from hour to hour, ranging from 800 kWh/t to over 1400 kWh/t. By looking at the original data, we concluded that this variability was due to fluctuations in both the numerator (motor load) and the denominator (throughput). Sometimes one of the two reject refiners was stopped, but the number of reject refiners in operation was not always a function of the number of working TMP lines.

Though based on several assumptions, this estimate of specific reject refining energy showed significant correlation with the pulp quality at the refined rejects outlet, much more so than the original variables did. This was true for both bivariate (cross-correlation) and multivariate (MVA) statistical tests, as shown in Figure 4.5 for fibre length. Note that the calculated specific reject refining energy dominates the MVA plot in 4.5b (second column from the right) despite the presence of the original variables from which it was directly calculated.

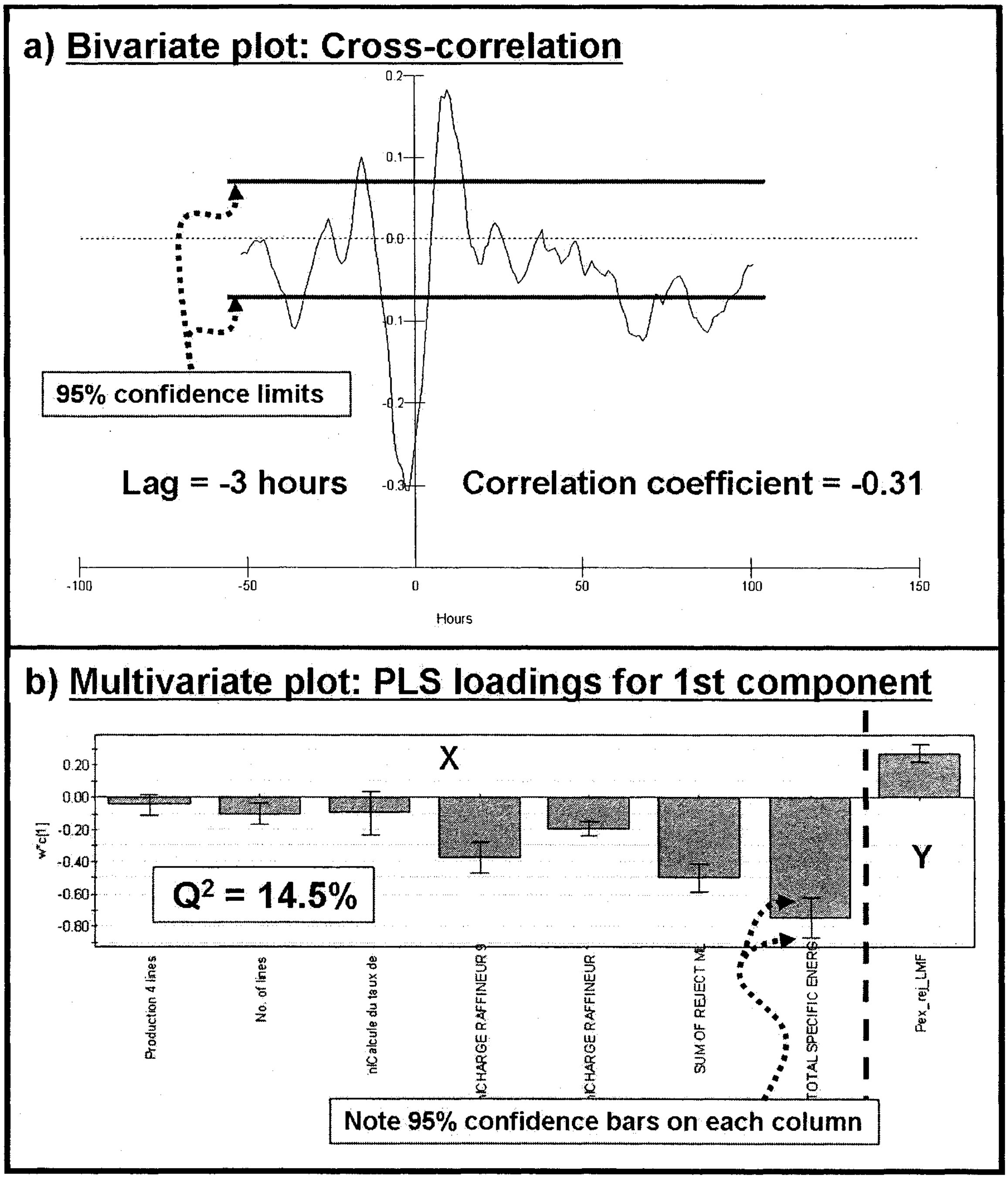

Figure 4-5: Statistical relationship between specific reject refining energy (calculated from other variables) and pulp quality at the refined rejects outlet. 2a) bivariate plot, showing the cross-correlation between reject specific energy and fibre length, August 2003. 2b) corresponding multivariate score plot showing all the reject variables.

In each case, the amount of variability explained is not particularly high: a correlation coefficient of 31% in one case, and a Q^2 of 14.5% in the other. This is not surprising, since reject refining is only part of the overall picture. The point is that these correlations, though small, are statistically significant as indicated by the 95% confidence limits on both plots.

MVA is not a time series technique, and treats all observations as separate events. Process lags must therefore be synchronized beforehand. At the case study mill, the process lags for the mainline pulp are not constant because of changes in tank levels. However, for the purposes of this study the monthly average lags between unit operations were used. These were estimated by comparing cross-correlation curves, in this case for fibre length measured at different points in the process, as listed in Table 4.6.

Table 4-6: Average process lags used in PLS model, based on cross-correlation curves for average fibre length at various locations, for August 2003.

Location	**Lag**
Based on cross-correlation curves:	
Headbox feeder tank	0 h
Disk filter feed	-2 h
Refined rejects outlet	-3 h
Primary screen accepts	-5 h
Outlet of latency chests	-5 h
Assumptions, by simple extrapolation:	
Final paper	0 h
Reject refiners	-5 h
Primary and secondary refiners	-6 h

An attempt was made to link process lags to high density tank levels, but no statistically significant relationships could be found, probably due to the small number of datapoints available for any given tank level.

To model the final paper quality, it was necessary to combine all the different TMP sections into a single model. Our reasoning was to mimic as closely as possible what the pulp itself actually experiences, namely a total mixing of all TMP refining lines, plus the reject lines, with process lags and a dampening high-frequency fluctuations.

Initially, we created models in which the four TMP lines appeared separately. It became apparent that this approach led to serious problems. The models were exceptionally hard to interpret, because they tended to reflect the idiosyncrasies of the four individual lines, rather than the entire upstream effect on the pulp and newsprint. Thus, one week Line 1 might dominate, whereas for a different week it might be Line 3. Not surprisingly, these models tended to be weaker overall.

Before combining the four main TMP lines, each was first treated individually by removing all shutdown periods. Any hour during which the minimum production rate was below the threshold was systematically erased. The hour itself was not removed, but the values for production, specific energy and consistency were replaced with blanks. Combining the four main lines, therefore, consisted in taking the average of just those lines that were in operation for any given hour. This technique completely eliminated the effect of starts and stops, while giving the correct weighting to the lines in operation.

In the case of plate age this approach was unnecessary, because the plates do not age when the line is shut down. The ages for all four lines were simply added together. In order to differentiate between the different kinds of refiners, the four primary refiners were considered as one group, the four secondary refiners as another group, and the two reject refiners as a third group.

Due to frequent grade changes, the original plots of the tear and bursting strengths showed abrupt shifts not related to the upstream TMP process. This would have destroyed any chance of linking these two parameters to the refining section Dividing these two parameters by the basis weight, to create an index, greatly reduced this effect, underlining the importance of studying the original data before doing any MVA. Permeability was also clearly linked to basis weight, but in this case indexing was not helpful so the models were limited to periods of 45-g/m^2 production (roughly two-thirds of the hours) but only for this parameter.

Using this approach, it was possible to link pulp quality back to the TMP operations, including the reject refining, as shown in Table 4.7. When using real process data, it is common to have Q^2 values in the range of 40%, i.e., the model explains with statistical significance 40% of the Y variance. The unexplained portion of the variance corresponds to unmeasured (or unmeasurable) process variables that impact the paper quality.

Table 4-7: Summary of PLS models obtained using hourly averages for month of August 2003

PLS Model	Number of Components	Q^2
Pulp Quality (freeness, fibre length & fines content)	5	38%
Paper Strength (tear, burst & TSI)	3	47%
Porosity (permeability to air)	3	69%

Table 4.8 shows the TMP and reject operating variables associated with each of the dependent variables, in other words which X variables were grouped by the PLS model with the Y variables. For the most part, the trends that we found correspond to what would be expected for a typical TMP operation.

Table 4-8: Pulp Quality Model – TMP and reject refiner operating variables (X variables) most associated with each dependent (Y) variable. August 2003.

Sampling location	Y variables	X variables showing strongest correlation within PLS model
Outlet of refined rejects tank	Higher freeness	Lower specific energy in reject refiners.
	Higher average fibre length	Lower overall specific energy; lower refining consistency; older plates.
	Higher fines content	Higher overall specific energy; higher refining consistency; newer plates; fewer TMP lines in operation; higher motor load standard deviation.
Primary screen accepts	Higher freeness	Lower overall specific energy; lower refining consistency; older plates.
	Higher average fibre length	Lower overall specific energy; lower refining consistency; older plates.
	Higher fines content	Higher overall specific energy; higher refining consistency; newer plates; fewer TMP lines in operation; higher motor load standard deviation.

Using this multivariate approach, we were also able to find correlations between the upstream operations and the final newsprint. Table 4.9 shows which TMP and reject operating variables were statistically linked to each of the paper quality parameters. Again, the results are consistent with expectations.

Table 4-9: Pulp Quality Model – TMP and reject refiner operating variables (X variables) most associated with each dependent (Y) variable. August 2003.

Y variables	X variables showing strongest correlation within PLS model
Higher tear strength	Higher overall specific energy; higher refining consistency; newer plates; more TMP lines in operation.
Higher bursting strength	Higher overall specific energy; higher refining consistency; newer plates; more TMP lines in operation.
Higher TSI	Higher overall specific energy; higher refining consistency; newer plates; fewer TMP lines in operation.
Higher porosity (permeability to air)	Lower overall specific energy, esp. at reject refining; lower refining consistency; older plates; more TMP lines in operation.

The next phase was to study the temporal and spatial resolution of the model structure. Building on this previous work, we compared different timescales and combinations of unit operations, to determine which yield the best process simulations. To answer this question, we planned series of runs using data from different sections of the mill, different months, different years and different paper machines. These are listed in Table 4.10. Each PLS model had exactly the same, but with different Y's depending on the trial.

The detailed results of each trial are given in Appendix XII. The first set of graphs are the timeplots for each X and Y variable as used in the model. The next set of graphs are the PLS scores and loadings for each individual scenario from Table 4.10. Possible interpretations of the different components have been added to the plots, based on process knowledge and experience using the PLS algorithm.

Table 4-10: Grid of PLS models, showing results for each. The first number in each box is the Q^2 obtained for the overall model, i.e., for all the Y variables taken together. Values above 40% are in bold. The second figure is the corresponding number of principal components.

		X	Y:	Pulp	Y: Paper - Machine A			Y: Paper - Machine B		
		Pulping section operating variables	**Outlet of pulping section**	**Feed to paper-making section**	**Strength**	**Porosity**	**Linting**	**Strength**	**Porosity**	**Linting**
March 2003	**1 h**	✓	38% 4 comp	36% 4 comp	27% 4 comp	30% 2 comp	§	**44%** 4 comp	**47%** 3 comp	§
	8 h	✓	38% 3 comp	19% 2 comp	*0%* *0 comp*	**58%** 1 comp	§	27% 3 comp	**53%** 2 comp	§
	24 h	✓	17% 3 comp	21% 2 comp	*0%* *0 comp*	**43%** 1 comp	§	*0%* *0 comp*	38% 1 comp	§
August 2003	**1 h**	✓	38% 5 comp	33% 4 comp	**47%** 3 comp	**69%** 3 comp	§	20% 2 comp	26% 2 comp	§
	8 h	✓	18% 3 comp	17% 2 comp	26% 2 comp	**50%** 1 comp	§	11% 2 comp	37% 2 comp	§
	24 h	✓	10% 1 comp	13% 2 comp	30% 1 comp	**57%** 1 comp	§	6% 1 comp	30% 2 comp	§
March 2004	**1 h**	✓	**44%** 5 comp	**42%** 5 comp	32% 3 comp	**46%** 4 comp	§	26% 3 comp	17% 2 comp	§
	8 h	✓	34% 2 comp	16% 1 comp	20% 2 comp	8% 1 comp	§	12% 1 comp	21% 1 comp	§
	24 h	✓	26% 2 comp	*0%* *0 comp*	*0%* *0 comp*	*0%* *0 comp*	§	12% 1 comp	*0%* *0 comp*	§
August 2004	**1 h**	✓	**64%** 5 comp	**68%** 5 comp	**53%** 5 comp	**63%** 2 comp	**52%** 2 comp	**37%** 4 comp	**60%** 2 comp	38% 4 comp
	8 h	✓	37% 1 comp	**44%** 3 comp	*0%* *0 comp*	**51%** 1 comp	35% 1 comp	*0%* *0 comp*	**70%** 2 comp	15% 1 comp
	24 h	✓	**48%** 3 comp	*0%* *0 comp*	13% 1 comp	**52%** 2 comp	28% 1 comp	*0%* *0 comp*	**56%** 2 comp	9% 1 comp

§ No data available for that month.

The results of the PLS simulation technique for each process scenario are summarized in Table 4.11. As we would expect, the best models were for the pulp sampled immediately downstream of the refining section, followed closely by the pulp from further downstream. The only exception is August 2004, where the downstream pulp shows a slightly higher Q^2. The newsprint quality models were somewhat poorer, very much so in some cases. Among the newsprint models, paper strength gave the best models, with a greater number of components, indicating a higher degree of detail. However, porosity and linting also showed fairly good models in many cases.

Table 4-11: Summary of one-hour PLS models obtained for entire grid, showing range of results

Type of PLS Model (Y variables)	**Number of useful principal components**	**Range of Q^2**	**Dominant upstream parameters (X variables)**
Pulp Quality – Outlet of pulping section	4 to 5	38% to 64%	Plate age, specific energy, consistency, motor load variability (Reject Specific Energy quite prominent)
Pulp Quality – Feed to papermaking section	4 to 5	33% to 68%	Plate age, specific energy, consistency, motor load variability (Reject Specific Energy quite prominent)
Paper Strength (both machines)	3 to 5	20% to 54%	Specific energy, plate age, # of lines, consistency, motor load variability
Porosity	2 to 4	17% to 63%	Plate age, specific energy, # of lines, instability, motor load variability
Linting (August 2004 only)	2 to 4	38% to 52%	Specific energy, consistency, plate age

There appears to be a link between the quality of the pulp models for a given month, and the quality of the corresponding paper models, although this trend is by no means linear. It is well known that certain pulp parameters are determinant for paper quality (Law, 2005; Saltin and Strand, 1995; McDonald et al., 2001) but because of infrequent measurements taken by automatic samplers, an occasional lack of direct correlation is to be expected. In fact, in some cases the paper models were actually better than the corresponding pulp model.

In general, the 1-h models were the best (highest Q^2) and most detailed (highest number of components) followed by the 8-h models, and then the 24-h models. The 8-h models had a similar overall structure to those for 1 h. However, there tended to be fewer components, indicating a less detailed model. The dominant X's (those with the highest PLS weightings, known as 'loadings') tended to be very similar to the 1-h case, meaning that little or no new information about the process could be gleaned at the 8-h timescale.

For the 24-hour averages, the Q^2, number of components and dominant X's tended to be quite similar to the 8-h case. However, the uncertainty bars are much larger, sometimes many times the size of the PLS loading itself, no doubt because so few points were used to create the model. For some of the 8-h and 24-h models, zero components were found, i.e., no statistically significant PLS model could be generated. This is despite the fact that significant models had been generated using the 1-h data. In such cases it seems that the use of the longer timescale destroyed the useful information within the dataset, perhaps by filtering out any interesting trends.

In two cases, the Q^2 for porosity was highest at 8 h, but in two other cases the opposite was found, namely the 8-h model was the poorest compared to the 1-h and 24-h models. When plotted against time, porosity shows a great deal of variability, much more so than for strength or linting. It would appear that this parameter's idiosyncratic behavior from one month to the next determines which time increment will yield the best model.

Because these were real operating data, with no experimental design of any kind, it is possible that some of the correlations were attributable to mere coincidence. We therefore used time-series and other mathematical techniques to evaluate the accuracy of our models.

Two examples of possibly coincidental results were considered. The first, involving a plate change, appeared to be a genuine correlation with paper quality, based on various time-series analyses, and a comparison of differently structured PLS models drawn from the same database.

The second example from Table 4.10 is "Paper Strength, Machine B, 1-h, August 2004". The original model had a Q^2 of 37% with 4 components. However, it can be seen that there is a calibration problem with Tensile Stiffness Index (TSI) during that month, as shown in Figure 4.6. Only the 'Machine Direction' values were affected (i.e., measured in the longitudinal axis of the paper sheet), whereas the paper machine 'Cross Direction' (perpendicular) measurements seem unaffected.

The first component shown in Figure 4.7 makes it clear that coincidence is at play. Plate age dominates, but all the other variables that are known to be critically important to the process (such as specific energy) are greatly under-represented. This would suggest that the routine changing of the plates that occurred during the month has been spuriously correlated to Tensile Stiffness Index. To remedy this problem, we redid the model using only the data points before the calibration shift. The results are shown in Figure 4.8. This not only improved the Q^2, but also resulted in a much more logical first component, in which the specific energies and consistencies are prominently correlated with overall paper strength.

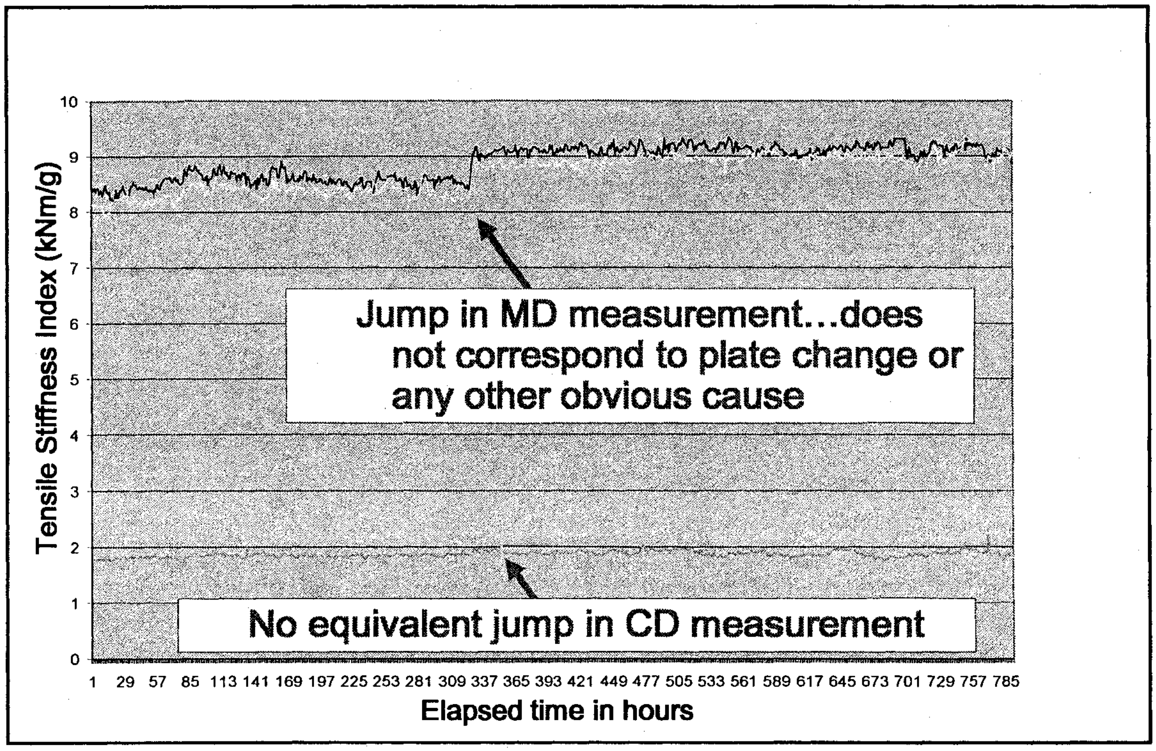

Figure 4-6: Calibration problem with TSI, Machine B, 1-h, August 2004.

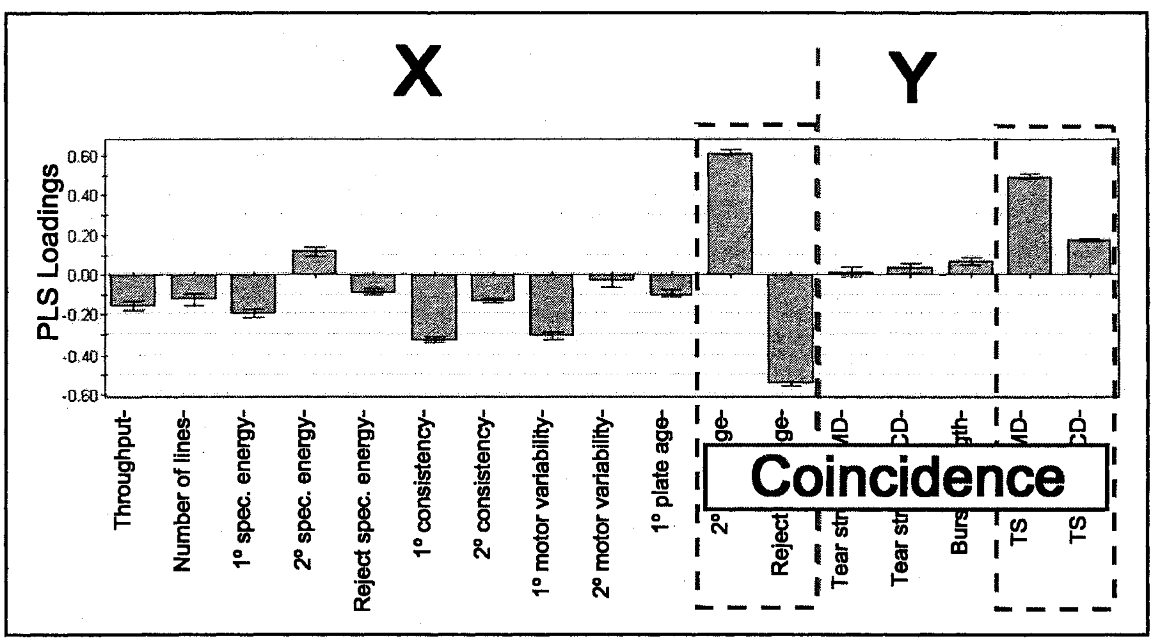

Figure 4-7: Component 1 loadings for Paper Strength, Machine B, 1-h, August 2004. Using corrupted TSI values

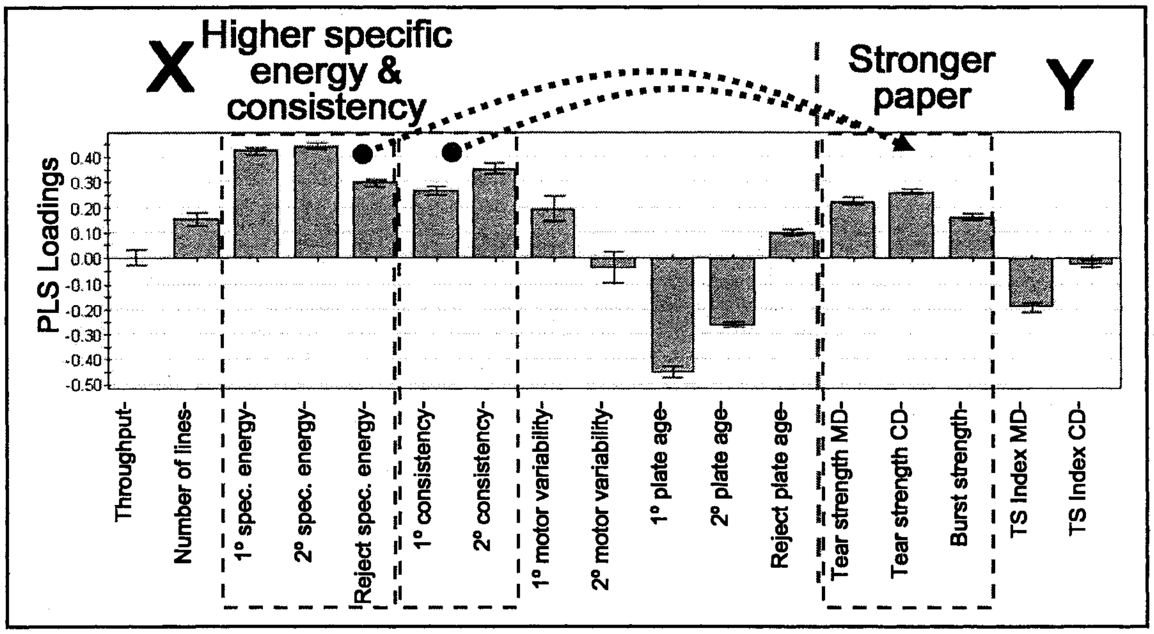

Figure 4-8: Component 1 loadings for Paper Strength, Machine B, 1-h, August 2004 Using correct values. Q^2 = 53% / 5 components

One goal for using MVA would be to automate the control of the TMP refiners to achieve the required pulp quality. Data from the papermaking section (longer loop) could be used to update the setpoints for pulp quality (shorter loop), as has been proposed in several commercial applications (Strand et al., 2001). To this end, it is possible to represent a PLS model in the form of a classic regression equation, even though this is not the real structure of the model but rather a one-off derivation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots$$

The results for our case study are given in Table 4.12, for August 2003. The coefficients for the same month of the following year are also shown, along with the percent difference. There is an enormous change, in the order of several hundred percent for many of the coefficients. Clearly, then, an adaptive model of some kind would be required to control the process. Based on our experience, we believe the coefficients would have to be updated at least once per day in order to follow the process adequately. Also, it would be preferable to have several sets of equations to cover known process scenarios such as new plates in the refiners.

Table 4-12: PLS regression coefficients for Bursting Strength in kPa/(g/m^2), Paper Machine A.

Symbol	X variable	Coefficients for August 2003	Coefficients for August 2004	Percent difference 2004 vs. 2003
B_0	Constant	6.8E-01	1.6E+00	133.8%
B_1	Production rate	8.2E-05	4.6E-05	-44.6%
B_2	Number of TMP lines in operation	2.0E-02	9.4E-03	-54.0%
B_3	1° specific refining energy	1.4E-04	7.6E-05	-46.2%
β_4	2° specific refining energy	2.3E-04	2.3E-04	-1.1%
β_5	Reject refining specific energy	1.4E-04	-7.0E-05	-151.2%
β_6	1° blowline consistency	-2.2E-03	-1.1E-02	384.1%
β_8	2° blowline consistency	-1.5E-03	3.5E-03	-328.3%
β_9	Standard deviation of motor load (1°)	-3.6E-01	2.1E-02	-105.9%
β_{10}	Standard deviation of motor load (2°)	3.9E-01	2.7E-01	-29.9%
β_{11}	1° plate age	-3.3E-06	1.4E-05	-509.9%
β_{12}	2° plate age	7.2E-05	-2.7E-05	-137.4%
β_{13}	Reject plate age	-5.6E-06	-2.0E-05	249.5%

Again, no bump tests or experimental design were used to generate our models. They were entirely based on pre-existing production data. It is therefore impossible to know if each variable is correctly represented. There might be an arbitrary split of coefficient weightings between two variables, which works well for the case at hand, but would be erroneous under other circumstances. It is likely that this explains why the percent differences in Table 4.12 are so large; they contain not only the difference between the different years, but also some random differences inherent to the method used.

CHAPTER 5.0 GENERAL DISCUSSION

Historical operating data, while a promising source of insight, can be difficult to use due to outliers, noise, and the multivariate nature of the process itself. MVA is a cheap, non-intrusive method for treating such data, but interpreting the results and avoiding findings that are merely coincidental can be quite difficult.

To address the MVA challenges outlined in the previous chapters, we have elaborated an overall methodology for performing MVA modeling on systems with multiple processing lines and infrequent product sampling. The major steps are illustrated in Figure 5.1, and described in the paragraphs that follow.

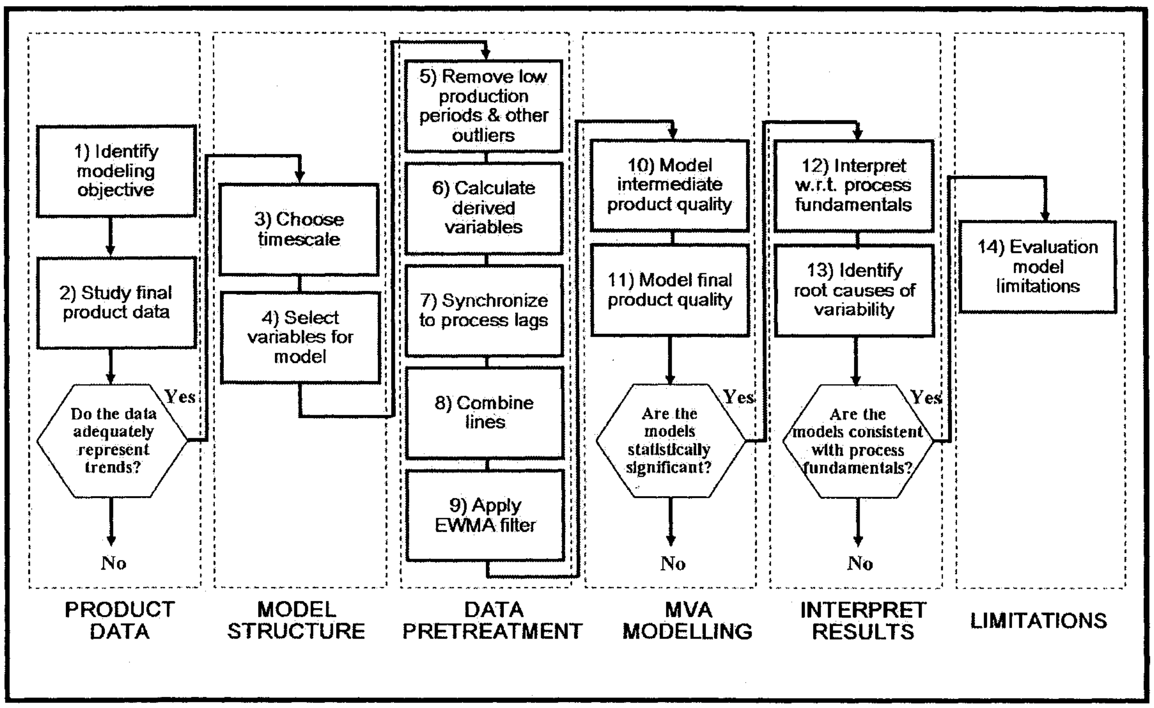

Figure 5-1: Proposed overall methodology for MVA modeling with multiple processing lines and infrequent product sampling.

In summary, the methodology consists in defining the modeling objective, studying product data, building a suitable model structure using known process fundamentals, pre-treating the data, creating the models with MVA, interpreting the statistical results, and finally identifying the limitations of the models. The goal is to obtain results that are not only statistically significant, but also physically interpretable.

Step #1 is to define the objective of the modeling activity, and clearly state the objective of the model in the context of the process, whether it be estimating the product compositions in a distillation column, or controlling a wastewater treatment plant. The modeler should use process and other knowledge to determine whether data is available for the set of X variables likely to affect the set of Y variables.

Step #2 is to study the dataset for final product quality, before doing any kind of statistical analysis. Some data sources are 'rich', with frequent, plentiful data that represent well the underlying process, while other data sources are 'poor', with infrequent grab sampling, often limited to a handful of parameters. The richness of the product quality data must adequately reflect the trends of interest. The most basic question is whether the right parameters are being measured. The type of equipment used to obtain each measurement must be understood, along with its maintenance and calibration schedules. Plotting each parameter over time can serve to highlight outliers, noise, missing data, overly compressed data, and other problems. Power spectrum and other time-series techniques can be used to ensure that measurement frequency sufficiently represents the variability of each key parameter.

Step #3 is to choose a base timescale. Modern data historians update the values every few seconds, but there is no point modelling at this timescale if the product quality parameters of interest are only measured, say, every few hours. The base timescale must be a compromise between these two extremes. As required, the user can also select multiples of the base timescale to represent slower trends in the process, or to correspond to the time constants of certain parts of the plant. The timescale choice must include a linkage with the overall objectives of the MVA model, such as whether the goal is fast control applications (thus seconds or minutes) or more long-term product quality control (hours) depending on the application.

Step #4 is to select key process variables which alone or in a non-linear combination represent best the process fundamentals. The measurements taken directly from the process instruments are not always 'fundamental', and since MVA is a linear mathematical technique it is important to ensure that the variables are selected and combined in such a way that the actual underlying process is being represented as much as possible. This step can require a profound understanding of the process being modeled. Merely choosing a list of convenient measurements and putting them together could result in an MVA model that is statistically significant, but devoid of useful meaning.

Steps #5 through 9 relate to data selection and pre-treatment. These steps include systematically removing dubious periods of operation such as low production and aberrant process behavior, calculating derived variables that are representative of the process fundamentals, synchronizing the data to account for process lags, combining upstream production lines, and filtering. A detailed illustration of the various steps is presented in Figure 5.2.

Step #5 is to remove all periods of low production and other major outliers, otherwise they will disrupt any useful information in the dataset. Significantly better PLS models were obtained when mill data were pre-treated as follows:

- the most stringent removal of low-production periods, namely ensuring that no second-by-second data point during the entire hour fell below the threshold, and
- major outliers identified on the PCA score and distance-to-model plots were systematically removed.

Step #6 is to calculate the derived variables, based on the logic described above. For instance, in the case study, specific refining energy and refiner consistency were not measured directly, and had to be calculated from other existing variables.

Step #7, synchronization of process lags, is necessary because MVA is not a time-series technique, and will automatically associate whatever data happen to appear within the same observation. Process lags can be determined based on flowsheet knowledge, plus time-series techniques such as cross-correlation curves. In the absence of plug flow, these remain gross approximations, however for the case study they were deemed adequate given the slowness of the paper quality trends being studied.

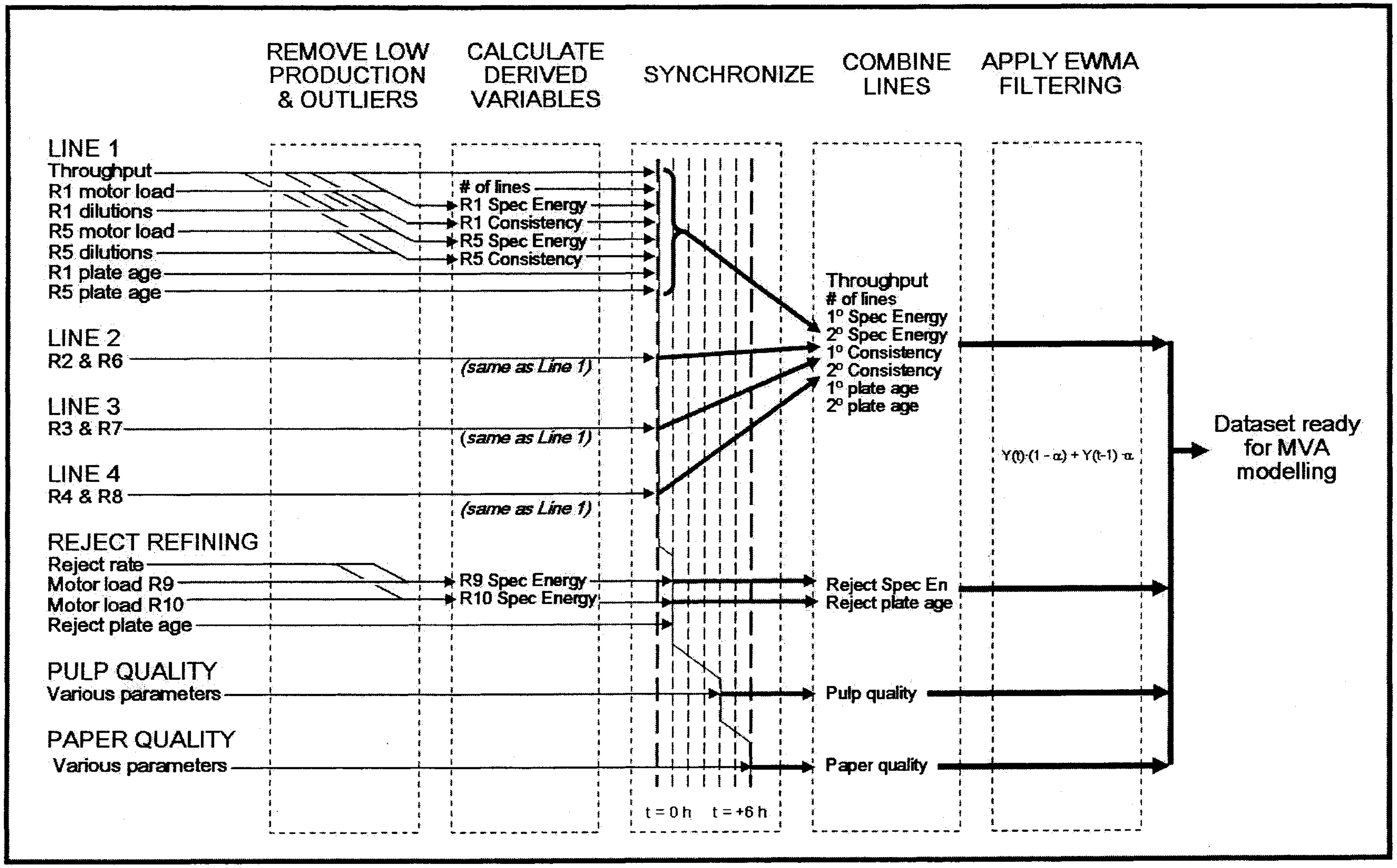

Figure 5-2: Data pre-treatment steps applied to TMP mill

Step #8 is combining the lines, which is necessary to avoid having idiosyncrasies in any one line dominate the model; our reasoning was to mimic as closely as possible what the product itself actually experiences, which in this case is a total mixing of all refining lines before proceeding to the papermaking section.

In Step #9, filtering is applied. Merely using a one-hour average is already a form of filtering, but we also applied EWMA filtering to all X and Y variables to smooth out spikes. The filtering coefficient (α) should be selected to match roughly the overall residence time of the process, again with the aim of mimicking what the product itself actually experiences.

Steps #10 and 11 are the creation of the MVA models for the intermediate and final product quality (Y variables) based on the process variables (X variables). With modern software, this part is quite straightforward.

Step #12 is the interpretation of the results with respect to process fundamentals. This is without doubt the most challenging part of the methodology, and requires a good deal of process knowledge and insight into the underlying process principles. MVA models are statistical, and if not built and interpreted carefully, can give no hint about linkages to the underlying physical phenomena which are of value to the modeler.

Step #13 is to identify the root causes of variability in the final product quality. Using the models based on process fundamentals, the purpose is to identify the upstream causes of the variability encountered in the intermediate and final products, to the extent that the data will allow.

Because MVA is a "black-box" technique, it is very important to determine the limitations of the results, Step #14, notably with respect to the operating regimes under which they were obtained. We may also be able to identify data gaps which, if addressed, could shed more light on the causes of product quality fluctuations. Adding or removing variables from the PLS models, dividing into shorter time periods, and using time-series techniques can help determine whether the findings are representative of the process, or merely the result of coincidence.

Although derived from our work on TMP newsprint data, the overall approach could be generalized to other process applications. The TMP newsprint mill under study can be represented in a generic fashion, as shown in Figure 5.3. It may thus be described as a two-step process, with a poorly characterized raw material, multiple upstream processing lines experiencing frequent starts and stops, and infrequent grab sampling of the intermediate and final products.

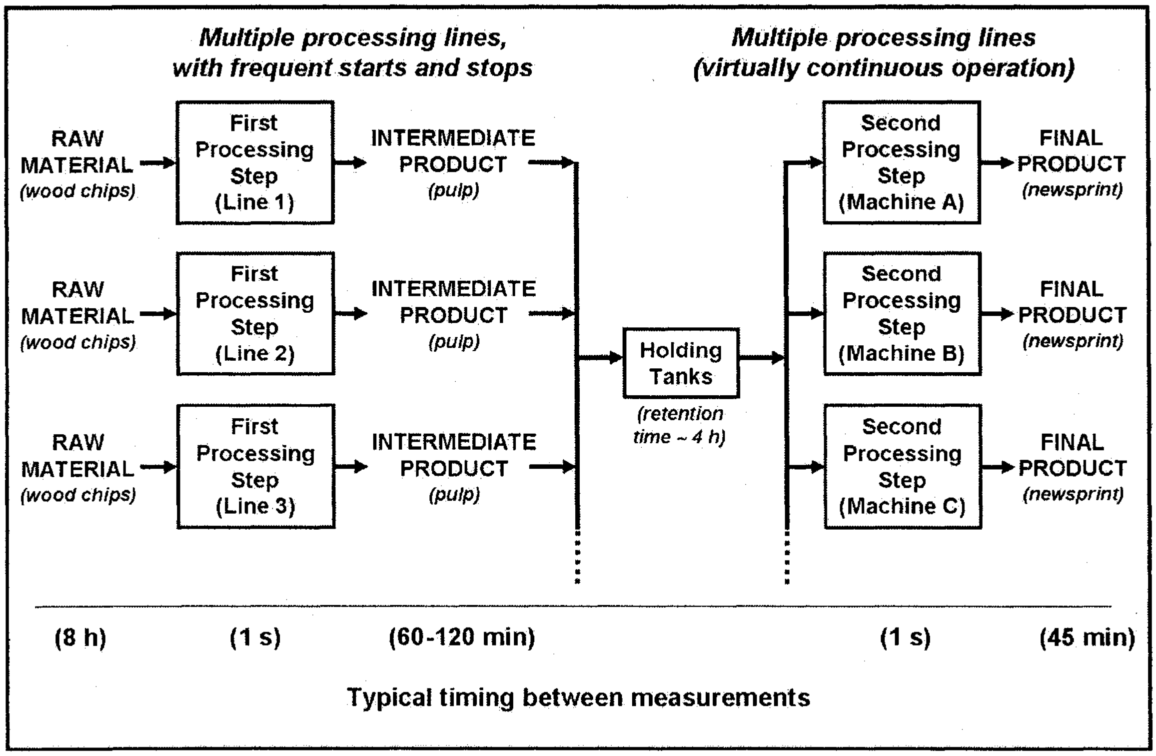

Figure 5-3: Generic representation of the case study mill.

Regardless of the application being considered, to capture the process dynamics adequately requires an overall approach that accounts for data lags, data filtering, and time averaging. The goal is to lag and filter the upstream variables in a sort of simulation of the process dynamics, so that they will be synchronized with each other and, more importantly, the final product properties.

Dynamics can be approximated by pure time delays, or time lags and time constants. For our case study, we assumed a overall transport lag from chips to paper of 4-6 hours, and adjusted the filtering coefficient accordingly. This is a highly idealized assumption, given the lack of plug flow, the presence of recycle loops, and fluctuations in holding tank levels. Process knowledge, combined with cross-correlation curves for key pulp parameters, served to estimate the time delay between various measurement points in the flowsheet. We used averaged values for these delays, taken over a period of days. For this application, it was unnecessary to represent the dynamics more accurately, because the paper quality variations under study were mostly long term. If the modelling objectives were more short term, it might be useful to try to link process lags to the holding tank levels.

Other techniques for dealing with process dynamics with MVA could the use of a autoregressive model structure, in which previous Y values are included as X variables. This is good for prediction, but not good for troubleshooting. Another possibility would be to introduce lagged X variables, which adds complications and may make the model difficult to interpret.

In short, any MVA modeling of industrial production data must deal with process dynamics. Other observations arising from our work include:

- MVA is a least-squares technique, and thus highly sensitive to outliers. Process lags must also be taken into account beforehand, otherwise the MVA algorithm will compare unrelated time periods.
- The timescale choice must include a linkage with the overall objectives of the MVA model. It is important to characterize which data sources are 'rich', with frequent, plentiful data, and which are 'poor'.
- Since MVA is a linear mathematical technique, it is important to ensure that the variables are selected and combined in such a way that the process fundamentals are reflected as much as possible.
- Care must be used when interpreting MVA results, such as assigning cause-and-effect relationships. This is especially true of variables affected by control loops.
- No bump tests or experimental design were used to generate our models, which were entirely based on pre-existing production data. It is therefore impossible to know how accurately each individual variable was represented.

These results confirm that MVA is a powerful tool for studying process data when provided with a suitable model structure, data that is free of major outliers and process disruptions, provision for the process dynamics, and a framework for interpreting the results that relate to physical reality.

CHAPTER 6.0 CONCLUSION AND RECOMMENDATIONS

Multivariate Analysis (MVA) is widely used for troubleshooting, monitoring and controlling industrial processes, and has become easily accessible to plant engineers through desktop software packages. However, this statistical technique remains highly susceptible to the adage "garbage in, garbage out". Production data are rife with outliers, instrument drift, starts and stops of key unit operations, and often product quality sampling is relatively infrequent.

The pulp and paper sector, like many globalized industries, finds itself with an increasingly demanding clientele who continually expect a better and cheaper product. An important design strategy for addressing this objective is the analysis of the vast quantity of process and product data accumulated in plant-wide data historians. Mill processes are multivariate, meaning that the interactions between the variables are as important as the variables themselves, so to extract the maximum benefit process relationships must be modeled as a group.

Using a Thermo-Mechanical Pulp (TMP) newsprint mill in Eastern Canada as a case study, we have developed some general recommendations for the application of Multivariate Analysis to historical operating data. These include:

- Data pre-processing techniques
- Methods for reflecting non-linearities in the MVA model
- Choice of timescale for the models
- General tests for possible coincidental relationships

One major conclusion was that models generated using an MVA variant known as Partial Least Squares (PLS) were significantly improved by pre-treating the data, with respect to both statistical significance and physical interpretability. We recommended an overall approach for applying MVA to industrial operating data, involving a systematic method for removing dubious periods of operation such as low production and aberrant process behavior, and filtering of all variables.

While data pre-treatment is clearly essential to successful application of MVA, these methods are generally compromises, and there is no one single "best" data pre-treatment methodology. However, in our study the models using pre-treated data were better, whether evaluated using statistical metrics or qualitative tests.

Periods of low production and other major outliers must be systematically removed, otherwise they will eclipse any useful information in the dataset. MVA is a least-squares technique, and is inevitably drawn to modeling the most extreme trends in the data. Our case study provided a good challenge in this regard, because of the poor quality of many of the data sources. Studying ordinary timeplots is important, because normalisation inflates impact of minor variations. Unfortunately, data on the incoming wood chips were extremely sparse, and were found to contribute little to the MVA models.

Exponentially weighted moving average (EWMA) filtering was applied to all variables to smooth out spikes. The filtering coefficient was selected to give a time constant of 4 h, which matches the overall residence time of the mill, which is roughly 4 to 6 hours from chip feeding to final paper rolling. The EWMA filtering has two advantages, the elimination of measurement noise, and approximation of process dynamics.

One possible explanation for the success of EWMA filtering is that MVA is not a time-series technique, and treats all datapoints as individual observations regardless of how close or far apart they are in real time. Filtering with EWMA essentially overlays time-related information onto the dataset, introducing a dynamic element not present in the original, unfiltered data. By providing the algorithm with more information about the system, filtering improves its ability to find correlations between X and Y variables. The filtering did not appear to affect which variables were the most prominent, suggesting that even with a high level of filtering, the model was still representative of the original data.

Synchronizing the variables at different points in the process is necessary because MVA will automatically associate whatever values appear within the same 'observation'. What we proposed was to lag and filter the upstream variables to simulate the process dynamics, so that they will be synchronized with each other and, more importantly, with the final paper properties. Process lags were determined based on flowsheet knowledge, plus time-series techniques such as cross-correlation curves.

In reality, transport lag from chips to paper is dynamic because of fluctuating tank levels. We found it best to use average values, however, because the data proved too sparse to follow the tank fluctuations over the short term. For the purposes of the case study there was no need to represent the dynamics more accurately, because the paper quality variations under study were mostly long term.

MVA models are basically a linear combination of the original variables. To reflect non-linearities in the real process, it is best to create new variables that correspond to process fundamentals. For instance, it is well known that certain pulp parameters are determinant for paper quality, such as specific energy, which is the central parameter of refiner operation. It must be high enough to ensure fibre separation and defibrillation, but low enough to avoid excessive fibre cutting which can adversely impact the strength of the final paper.

Refining intensity is much more difficult to measure in an industrial refiner. For a given plate configuration and disc rotation speed, refining intensity is largely a function of refining consistency, which was the parameter used in the case study. Finally, plate age is known to be a major factor, since the refiner plates wear out gradually, changing the shape and depth of the grooves on their working surfaces and thus the refining conditions experienced by the pulp.

The MVA user has a choice of timescales ranging from seconds to days. Based on the sampling frequencies for pulp and paper quality, we selected a base timescale of one hour. To make sure this was a valid choice, we performed power spectral density for key paper quality variables, and found that most variability occurs at periods greater than 10 hours, which is logical considering that most paper parameters are tightly controlled with control loops at the paper machines.

Using Multivariate Analysis and other statistical tools, it was possible to link product quality back to TMP and rejects operations, taking into account number of lines in operation, plate age and process lags. Use of a weighted-average filter helped to bridge the gap between the faster readings in the TMP section and slower paper quality trends. However, determining whether the correlations are attributable to coincidence is by no means obvious. Without a Design of Experiment, there is no way to ascertain whether the changes seen in two or more variables are fundamental or just happenstance. However, we can at least double-check whether our models stand up to scrutiny.

To this end, we studied the evolution of the process over time within the model space, to see how it behaved, and if any discrete events tended to dominate. We added and removed variables from the models, to make sure that the components we found were not just associated with a single (possibly coincidental) relationship. We also used a time-series techniques known as cross-correlation to investigate the nature of the correlations in the models.

Combining the lines is necessary to avoid having idiosyncrasies in any one line dominate the model; our reasoning was to mimic as closely as possible what the pulp itself actually experiences, which in this case is a total mixing of all refining lines before proceeding to the papermaking section. To validate this approach, we started with just a single refining line, then added all four lines together, then added the rejects refining, and finally included the final paper quality. In all cases, the combined variables performed better, and were easier to interpret, than the multitude of original variables. As discussed in Chapter 5, these findings could be generalized to other process applications, in particular to other cases where multiple production lines feed into buffer tanks that in turn feed multiple downstream lines.

A very important, and sometimes overlooked, part of any TMP mill is reject refining. Because the case study mill experiences frequent starts and stops on the four main refining lines, the throughput to the reject refiners is continually changing. The operators tend to increase the reject rate after a line stoppage, from approximately 30% to 40%, meaning that the fibre length distribution of the pulp entering the reject refiners varies over time. Combined with occasional stoppages of the reject refiners themselves, this situation results in a highly variable and poorly controlled reject refining.

We found significant statistical correlation between reject refining specific energy and pulp quality, notably for fibre length. It also featured quite prominently among the X variables for both the pulp and paper models. The reject refining specific energy was not directly measured, and had to be calculated from the motor loads of the two reject refiners and the rejects throughput. The values fluctuated between 800 kWh/t and 1400 kWh/t within a single month. Though based on several assumptions, this estimate of specific reject refining energy showed significant correlation with the pulp quality at the refined rejects outlet, much more so than the original variables did.

Overall, our findings allowed us to address the mill questions related to paper quality and process operation. With our approach, it was also possible to explain roughly half of the variability in final paper quality, in this case strength, porosity and linting. This is quite remarkable, considering that no paper machine operating variables were used, and that little or no data were available on incoming chip quality. Of course, these results are correlational and not cause-and effect; it is possible that both the TMP operations and the paper were being affected by a third, unmeasured factor, such as changes in incoming chip quality.

Based on the above results, we developed an explicit, detailed methodology for applying MVA to production data which addresses these challenges, as described in Chapter 5. Using this methodology, it was possible to use MVA to correlate roughly half of the variability in the pulp quality and in the final paper quality.

The lack of useful quality data for the raw material is a serious obstacle. Nevertheless, by considering only one TMP line at a time, it was possible to link pulp quality back to the upstream refining operations by means of multivariate statistics. The PLS models obtained were consistent with known process fundamentals, such as lower specific energy being associated with less fibre development (higher freeness) and less fibre cutting (longer fibre length and lower fines). The case study thus yielded results that were not only statistically significant, but also physically interpretable with regard to known process fundamentals.

With regard to season, no major differences were found in the models for winter versus summer months. Major seasonal swings could be seen when the entire year was studied using daily averages, but at the shorter timescales, the two winter months (March 2003 and 2004) and the two summer months (August 2003 and 2004) showed little in common.

As we would expect, the strongest models were for the pulp immediately downstream of the refining section, followed closely by the pulp further downstream. The newsprint quality models were somewhat weaker, very much so in some cases. There appears to be a link between the strength of the pulp models, and the strength of the corresponding paper models, although this was by no means consistent. Logically, the pulp quality must be related to the paper quality, since it is all the same wood fibre, and the literature review provides many examples. However, the statistical results from operating data do not always bear this out.

When comparing different timescales, the 1-h models were generally the strongest, followed by the 8-h models, and then the 24-h models. The 8-h models had a similar overall structure to those for 1 h, but tended to have fewer components indicating a less detailed model. For the 24-h models, the uncertainty bars are very large, sometimes many times the size of the PLS loading itself, no doubt due to the small number of observations used. The use of daily averages may not therefore be appropriate for capturing the faster dynamics of the pulp refining process.

In some cases, the PLS model for porosity was highest at 8 h, but in other cases it was the 8-h model that was the weakest. It would appear that this parameter's idiosyncratic behavior from one month to the next determines which time increment will yield the best model. This result would tend to justify the multi-timescale approach used.

Even our best models only explained 40% to 60% of the variance in the pulp quality, meaning that about half of the variance remained unexplained, and corresponds to unmeasured variables. Some of the various on-line wood chip monitors under development should help to address this data gap.

Because no single model was able to cover all process scenarios, it seems that some kind of adaptive controller would be required to automate the TMP refining process. To this end, it is possible to use PLS models to predict new Y values from new X values. However, there is an enormous change in the coefficients from one month to the next, in the order of several hundred percent. Planned experiments could help address this problem, but regardless of the process control application being considered, accounting for data lags, data filtering, and time averaging is critical to capturing the necessary dynamics.

Based on our experience, we believe the coefficients would have to be updated at least once per day in order to follow the process adequately. Also, it would be preferable to have several sets of equations to cover known process scenarios such as new plates in the refiners.

Finally, caution must be exercised before ascribing cause-and-effect to what are purely statistical outputs. Interpretation of black-box models is not straightforward, and requires a profound knowledge of the process in question. This caveat is relevant to other industrial operations facing similar data challenges.

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APPENDIX I:

Summary of MVA Papers Reviewed

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Author(s)	Type of MVA	Purpose	Key Findings	Additional Comments
Troubleshooting of TMP Process				
Saltin and Strand (1995)	Factor Analysis	To establish the influence of certain TMP properties on paper quality	Fibre length had a strong influence on tear strength, including CD tear strength	
Nobleza (1997)	PCA	Compare furnish, refining energy and quality variables from four TMP refining lines	The major contributors to strength variations were found to be chip source and chip size distribution	
Lupien et al. (2001)	PLS	Maximise Tensile Energy Absorption (TEA), tear strength and opacity.	Two-thirds of the strength variations were explained by paper machine variables.	MVA heavily slanted towards those variables which were measured better or more frequently
Browne et al. (2003)	Factor Analysis	Establish relationships between furnish and pulp properties	variability in pulp properties explained by wood freshness and ease with which energy could be applied to the wood	Care must be used when interpreting and assigning cause-and-effect relationships to the results
Elsinga (2002)	Factor Analysis	Address complaints from customers about paper linting	Freeness is not a good measure of pulp quality	Planned experiments were performed, using a 3-factorial design for feed rate, feed consistency and reject rate
MVA for Inferential Control				
Kooi (1994)	PLS	Create soft sensor for freeness in a wood chip refiner	Manipulated variables: plate gap, water dilution flow → input is plate gap, output is freeness	Does not appear to have ever been tested on a real refiner
Strand et al. (1998)	PLS	Implement soft sensors at two TMP mills	Success in decreasing off-specification paper, and eliminating the use of costly Kraft pulp	Control strategy first tested on a dynamic simulation, then later on real process

Strand et al. (2001)	PLS	Implement mill-wide advanced quality control (AQC) system which combines all four TMP lines	Full implementation of soft sensor at the Stephenville mill, with reduction in variability of freeness, average fibre length and shives	Soft sensors used for TMP mainline, TMP rejects and newsprint porosity; modelled variability as a new variable
Strand et al. (2005)	PLS	TMP refiner control at Augusta Newsprint	Millwide Quality Control system including 4 refiner lines, primary screens and reject refiners	
Other Pulp & Paper Applications				
Bendwell (2002)	PCA	Implement advanced process control of wastewater treatment plant	Successful on-line control of process	Justified use of 24-averages based on long retention times in wastewater basins
Kuusisto et al (2002)	Unspecified	Implement advanced process control of grade changes	Improved performance over manual operation	
Broderick et al. (1993, 1994 and 1995)	PLS	Implement advanced process control of chemical pulping	UHYS handsheet properties related to five latent variables: 1) available bonding area; 2) fibre swelling and bond strength; 3) fibre length and network continuity; 4) fibre elasticity; 5) fibre strength	Designed experiments
Wold and Kattenah-Wold (2003)	PCA and PLS	Implement advanced process control of chemical pulping	'Snaking' of time series data around the component space, as process changes	
Tessier et al. (2001)	PCA	Compare paper quality at 30 different mills	Mills with similar technologies cluser together in two-dimensional component space for paper quality	

Ivanov (2003)	PCA and PLS	Analyse process data from paperboard production line	Recommendations included setting 'out limits' to avoid extreme values, and maintaining residuals measured as "Distance to Model" (DModX) below 8 units	Author found it most effective to do PLS block analysis
Ritala et al. (1991)	Unspecified	Address problem of uncontrollable fluctuations in wet-end chemistry	Report success at using a computer-based diagnostic system for analysing different measured variables	
Tessier and Broderick (2000)	PLS	Several examples of MVA applications in pulp and paper	Chip size distribution for a UHYS plant, refiner pulp quality prediction and control, and the effect of refiner plate filing material on fibre development	In some cases the variables were manipulated in designed experiments
Shaw (2001)	Unspecified	Improve CD stiffness while reducing cost at an uncoated free-sheet machine	Report $2 million U.S. / year savings after data-driven optimisation project	Results in some cases opposite to prevailing wisdom at the plant
Champagne et al. (2002)	Neural networks and PLS	Create soft sensor at unspecified type of mill, to predict process stability and product quality	Best to follow process using DModX, Hotelling's T^2 (stability), and Contribution Plot (source of problem)	Using DModX, can tell when MVA model is no longer valid
Sarimveis (2001)	Neural networks and PLS	Create soft sensor for tissue softness, which cannot be measured in real time	Inferential sensors can be very useful in improving the performance of the tissue machine	
Phung (2003)	Neural networks and PLS	Create soft sensor for tear strength, which cannot be measured in real time	$ benefit can predict % Kraft required to attain tear property required	

Marklund (1998)	PCA and PLS	Compared different wood species and geography (pine and spruce)	Beating treatment most important parameter for Kraft pulp handsheet properties	Designed experiments.
Pre-Processing of MVA Data				
Hodouin et al (1993)	PLS	Statistical analysis of mineral processing data	Authors recommend using multiple-input-multiple-output (MIMO) for PLS process modelling, given that Y's are generally correlated; emphasise that MVA model only works within the domain where it was calibrated; models created under closed-loop conditions cannot predict open-loop behaviour	Included use of 'mass balance filters' to enhance data quality and the creation of new variables
Kresta (1994)	PLS	Develop of inferential process models for various industries	Open-loop data cannot be used to model closed-loop schemes; must continue to behave in a similar fashion as the original dataset	Authors state that scaling to unit variance does not adequately account for error
Zamprogna et al (2002)	PLS	Create soft-sensor for a batch distillation column	Authors emphasise importance of selecting appropriate model input variables, correctly addressing lagged measurements, and doing individual PLS models for each batch phase	Used linear and non-linear versions of PLS
Rosen et al (2001)	PCA	Wastewater treatment system	MVA not suited to monitoring processes with non-stationary behaviour, hence need for adaptive model	
Kourti (2003)	PCA/PLS	Acquistion and compression of multivariate data for batch processes	Batch processes, start-ups and grade transitions are dynamic and require alignment and synchronisation of 3-way data	

APPENDIX II:

Characteristics of Case Study Mill

APPENDIX II: CHARACTERISTICS OF CASE STUDY MILL

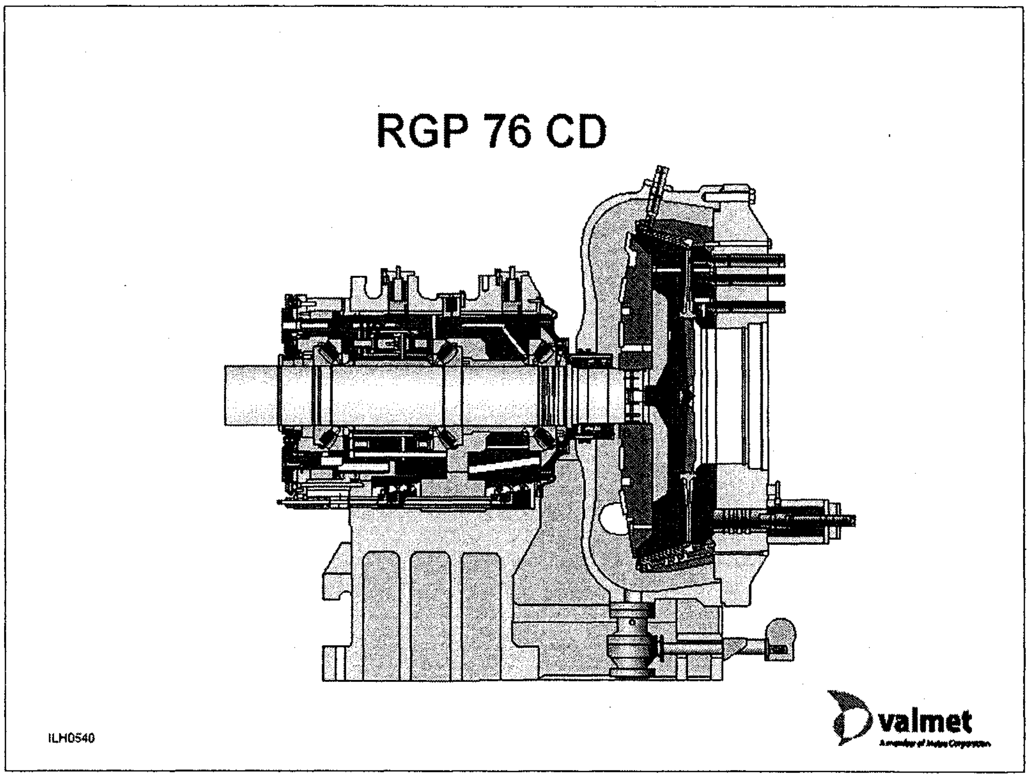
Prepared by R.P. Harrison, École Polytechnique de Montréal / April 2005

Basic Information

Year of Construction:	1926
Grades:	42-g, 45-g and 48.8-g newprint
Feed:	100% wood chips (no DIP since 2000) 4% aspen, 96% black spruce and/or balsam fir
Wood chip suppliers:	External, numbering 15-20
Boilerhouse fuel:	Bark, heavy oil
Employees:	600
TMP lines:	10 Sunds Defibrator RGP-70-CD conical refiners: • 4 lines of 1° & 2° refiners • 2 reject refiners, operating in parallel
Pulp screens:	Centrisorter Type 110B (8)
High-density storage tanks:	1 x 200 BDT 3 x 130 BDT
Paper machines:	No. 4: Dynaformer top-wire unit on Dominion Engineering Foudrinier, capacity 150 000 t/a No. 5: Valmet-Dominion Sym-Former, capacity 195 000 t/a
Bleaching:	Hydrosulphite, injected at 2° refiner

Refining Conditions - Sunds Defibrator RGP-70-CD Refiners

Main steps:	1. Steam pre-heating of chips at 180 kPa for 3 min 2. Primary refining at 350 kPa and 40-50% consistency 3. Secondary refining at 350 kPa and 40-50% consistency
Motor power :	18 000 HP (13 MW)
Rotor diameter:	Flat section: 54 in. (137 cm) Conical section: 16 in. (41 cm)
Angle of conical section:	70°
Nominal distance between plates:	1.2 -1.4 mm for the primary refiner 1.0 - 1.2 mm for the secondary refiner
Dilution water entry points:	Flat section Conical section (unused until January 2005)
Typical plate age:	2000 h
Plate direction change:	Every 200 h



Cutaway diagram of a Sunds conical refiner (later model)

Chip/Fibre Retention Times - Nominal

These are approximations, based on the P&ID's and discussions with mill personnel for 1000 t/d typical operation, with all lines in operation (reject, screen & cleaning loops excluded).

Plant Area	Unit Operation	Total Equipment Capacity	Typical Operating Level	Typical Retention Time
Chip Handling	Pile	3000 t per pile	2500 t	60 h
	Main feed to mill *("Conveyor 018")*			Time = 0
TMP Plant	TMP chip silo	45 minutes	50%	25 minutes
	Chip washing	≈ minutes	-	5 minutes
	1° ref. buffer hopper	3-5 minutes	-	5 minutes
	Refiners (incl. 2° hopper)	≈ minutes	-	5 minutes
	Latency chest	45 minutes	Over 90%	45 minutes
	HDP tanks	1 x 4.6 hours 3 x 2.8 hours	Highly variable	240 minutes (± several hours)
	Levelling tank	45 minutes	80%	35 minutes
Paper Machine	« Cuvier pâte pré-mélangée » / «… récup. des fibres »	8 minutes	75%	5 minutes
	« Cuvier pâte mélangée » / « …de la machine »	30 minutes	67%	20 minutes
	Headbox	≈ seconds		0
	Former/Press/Dryer	≈ minutes		5 minutes
TOTAL				6 h 30 min

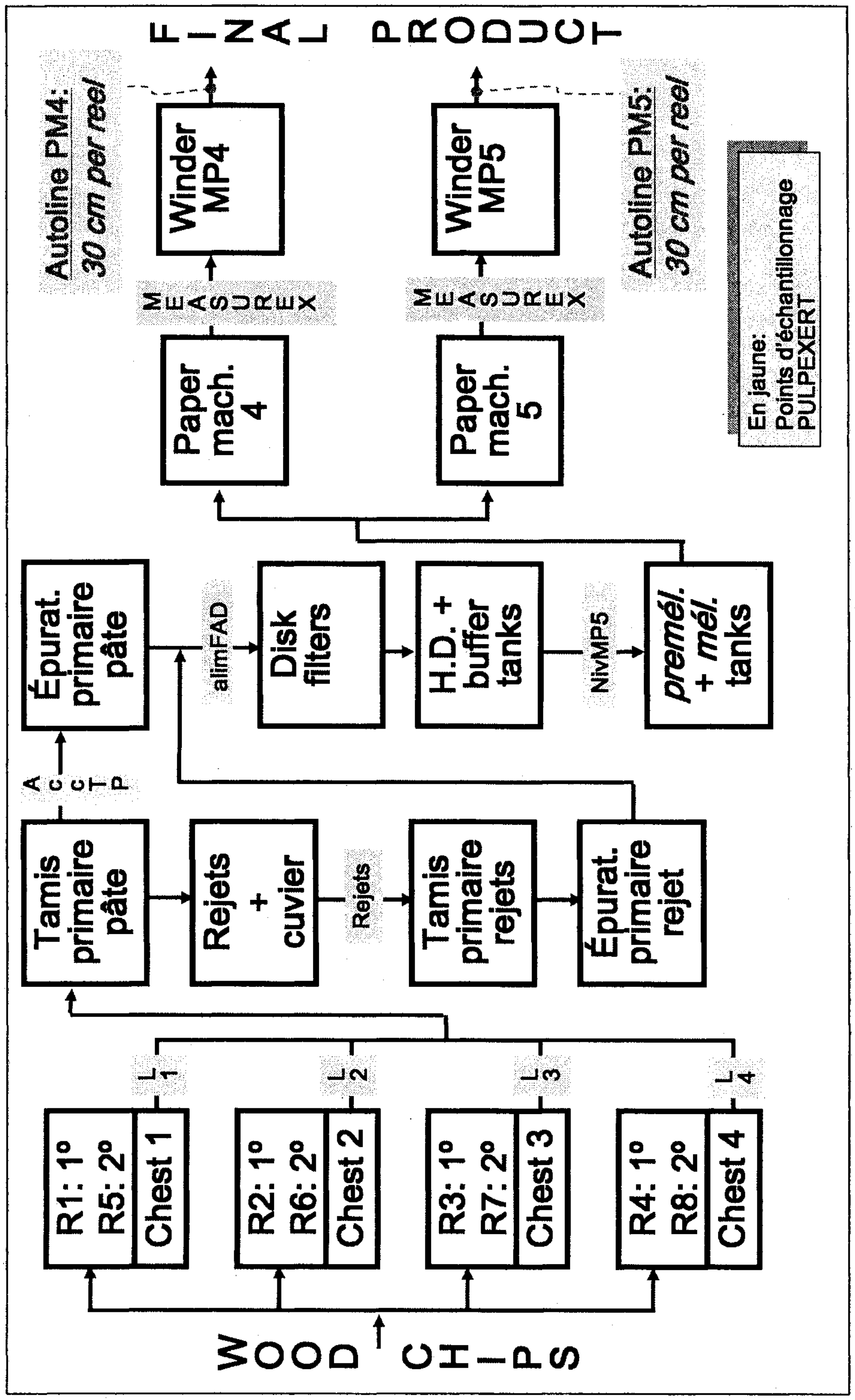
Paper Quality Targets

Parameter	42 g	PM 4: 45 g	PM 4: 48.8g	PM 5: 45 g	PM 5: 48.8g
Tear (mN) – max	-	290	300	300	340
– min	-	275	285	285	325
Burst (kPa) – max	-	63	80	68	80
– min	-	60	75	65	75
TSI MD (kNm/g)	8.1	8.1	8.1	8.1	8.1
TSI CD (kNm/g)	2.0	2.0	2.0	2.0	2.0
Permeability (mL/min)	350	300	300	300	300

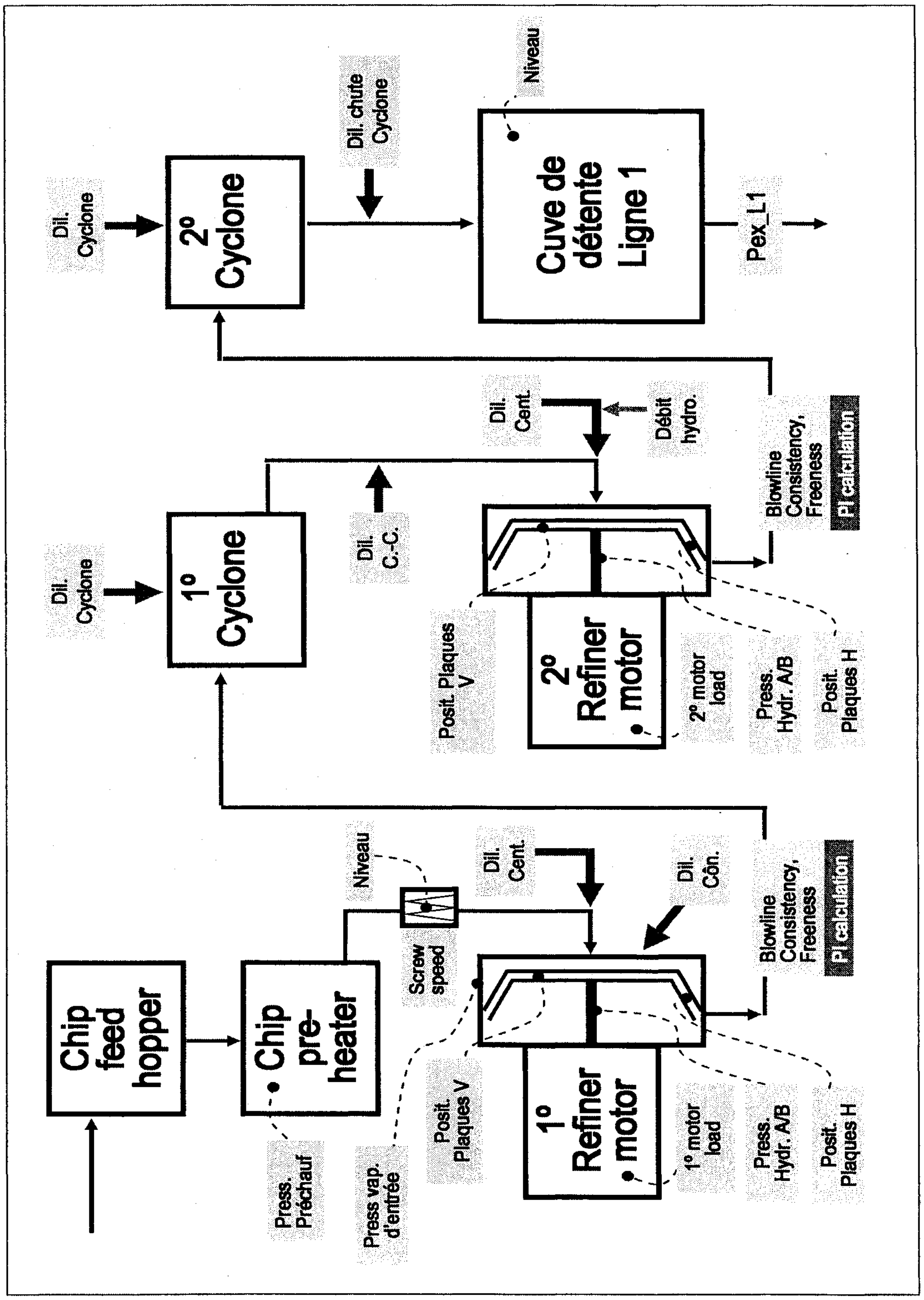
Paper Quality Targets

Parameter	Target
Freeness	210 ±10 CSF in 2° blowline
Average fibre length (length-weighted)	1.2 – 1.3 mm
Percent fines	Not specified

Overall Mill Flowsheet



Flowsheet for Refining Line 1 Only



APPENDIX III:

Chart of Operator Control Actions

APPENDIX III: CHART OF OPERATOR CONTROL ACTIONS

Prepared by R.P. Harrison, École Polytechnique de Montréal / April 2005, Rev. 4

Controlled Variable	Condition	Measurement Method	Dead Time	Manipulated Variable(s)	*Comments*
REFINER 1°					
1° Motor Load <u>Target</u> : 11 MW *(depends on species)*	↑ Too high > 12 MW	Electrical power of motor (MW)	< 1 min.	1) Verify if consistency is too high; if so, ↑ 1° central dilution; 2) If consistency is correct, ↑ *flat* plate gap V ; 3) If plates are at their limit, ↓ production.	*Feedguard triggers at 12,2 MW*
	↓ Too low < 9 MW			1) Verify if consistency is too low; if so, ↓ 1° central dilution; 2) If consistency is correct, ↓ *flat* plate gap V ; 3) If plates are at their limit, ↑ production.	
Consistency in 1° blowline MEASURED <u>Cible</u> : 50%-60%	↑ Too high > 60%	Two grab samples taken manually; laboratory test (% : average of 2)	1-2 h	1) ↑ 1° central dilution.	*If exceeds 70% pulp will burn*
	↓ Too low < 50%			1) ↓ 1° central dilution.	
Consistency in 1° blowline CALCULATED	Back-up for measured value	Mass/energy balance calculated by the DCS			*Not much used by operators*

Freeness 1° blowline MEASURED Target : 610 ±15 CSF	↑ Too high > 625 CSF	Two grab samples taken manually; laboratory test (CSF : average of 2)	1-2 h	1) Verify if consistency is too low; if so, ↓ 1° central dilution; 2) If consistency is correct, ↓ *conical* plate gap H.	
	↓ Too low < 595 CSF			1) Verify if consistency is too high; if so, ↑ 1° central dilution; 2) If consistency is correct, ↑ *conical* plate gap H.	
REFINER 2°					
2° Motor load Target : 10 MW *(depends on species)*	↑ Too high > 11 MW	Electrical power of motor (MW)	< 1 min.	1) Verify if consistency is too high; if so, ↑ 2° central dilution; 2) If necessary, adjust other dilution flowrates (1° cyclone and counter-current/bell); 3) If consistency is correct, ↑ *flat* plate gap V ; 4) If plates are at their limit, ↓ production at 1° refiner.	*Feedguard triggers at 12,2 MW*
	↓ Trop basse < 8 MW			1) Verify if consistency is too low; if so, ↓ 2° central dilution; 2) If necessary, adjust other dilution flowrates (1° cyclone and counter-current/bell); 3) If consistency is correct, ↓ *flat* plate gap V ; 4) If plates are at their limit, ↑ production at 1° refiner.	
Consistency 2° blowline MEASURED	↑ Too high > 60%	Two grab samples taken manually; laboratory test (% : average of 2)	1-2 h	1) ↑ 2° central dilution; 2) If necessary, adjust other dilution flowrates (1° cyclone and counter-current/bell).	*If exceeds 70% pulp will burn*

<u>Target</u> : 50%-60%	↓ Too low < 50%			1) ↓ 2° central dilution; 2) If necessary, adjust other dilution flowrates (1° cyclone and counter-current/bell).	
Consistency in 2° blowline CALCULATED	Back-up for measured value	Mass/energy balance calculated by the DCS			*Not much used by operators*
Freeness 2° blowline MEASURED	↑ Too high > 220 CSF	Two grab samples taken manually; laboratory test (CSF : average of 2)	1-2 h	1) Verify if consistency is too low; if so, ↓ 2° central dilution; 2) If necessary, adjust other dilution flowrates (1° cyclone and counter-current/bell); 3) If consistency is correct, ↓ *conical* plate gap H.	
<u>Target</u> : 210 ±10 CSF	↓ Too low < 200 CSF			1) Verify if consistency is too high; if so, ↑ 2° central dilution; 2) If necessary, adjust other dilution flowrates (1° cyclone and counter-current/bell); 3) If consistency is correct, ↑ *conical* plate gap H.	
OUTFLOW OF LATENCY CHEST					
Freeness – outflow of latency chest	Back-up for measurements at blowlines	Laboratory (broad range of pulp quality parameters)	24 h		
Freeness – outflow of latency chest	Back-up for measurements at blowlines	PulpExpert (CSF)	1-2 h		
Average fibre length – outflow of latency chest	↓ Too low	PulpExpert (mm)	1-2 h	1) Increase freeness, by adjusting controlled variables, especially at 2° refiner; 2) ↑ *conical* plate gap H at 2° refiner to avoid cutting of fibres;	*Causes:old plates; chip quality; low freeness;*

Target: > 1,2 mm				3) Verify plates, replace if too worn; 4) Check incoming chip quality.	*erroneous freeness measurements*
Fines – outflow of latency chest	↑ Too high	PulpExpert (% P200)	1-2 h	1) ↑ *conical* plate gap H at 2° refiner to avoid cutting of fibres.	

QUALITY PARAMETERS

SIMPLIFIED INTERACTIONS OF REFINER OPERATING VARIABLES

PRODUCTION BDMT/D	PLATE GAP MM	DILUTION L/MIN	REFINER CONSISTENCY %	LOAD MW	SPECIFIC ENERGY KWHR/T	FREENESS ML
↑	X	X	↑	↑	↑	↓
↑	↓	X	↑	↑	↑	↓
↑	↑	↑	X	↑	X	X
↓	X	X	↓	↓	↓	↑
↓	↓	↓	X	↓	X	X
↓	↑	X	↓	↓	↓	↑
X	X	↑	↓	↓	↓	↑
X	X	↓	↑	↑	↑	↓
X	↓	X	X	↑	↑	↓
X	↑	X	X	↓	↓	↑

CHANGE MADE BY OPERATOR   OBSERVED CHANGE   X NO CHANGE OBSERVED OR MADE

Chart of suggested control actions from Operator Manual in Control Room.

(scanned by Robert Harrison, April 2005)

Insights from Control Room Operator Manual (1 of 2)

(transcribed by Robert Harrison, April 2005)

At a constant production rate, reducing plate gap leads to higher specific energy. Higher specific energy results in higher steam pressure, both forward and countercurrent. The higher the consistency, the larger the plate gap must be to achieve the same specific energy. At a higher production rate, it is harder is to maintain the same specific energy level. The plate gap must be reduced, but this is difficult because the axial force required is higher. To increase specific energy, the operator will increase the consistency or reduce the plate gap. To reduce the refining intensity, the operator normally will have a tendency to increase the plate gap. At low consistency, one must reduce the plate gap to achieve the desired energy. By reducing the plate gap, the quantity of fibre between two bars that cross each other will be reduced and thus the refining intensity will increase. Higher consistency increases the residence time between the plates and thus reduces the refining intensity. At a higher consistency, we must operate with a larger plate gap for the same energy, which allows us to reduce the refining intensity.	A consistency that is too low leads to higher freeness; too high results in dry cutting which creates fines. If the operation does not achieve a higher ML by reducing the dilution or by closing the plate gap, this means that we are out of the optimum operating window and have moved to a condition of dry cutting of the fibres. Main quality goals: maintain freeness in target range; for a given freeness, maximise fibre length. In fibre length/freeness window, want to operate in upper left-hand corner (high length, low freeness corresponding to low refining intensity). Higher specific energy for the same freeness means the fibres have been more developed and are of better quality. Economy of scale: higher production rate means higher energy efficiency (energy required to achieve a given freeness and quality is lower). Too much energy will have a tendency to damage fibres by cutting them rather than by modifying the fibre surface. To reduce the freeness, we must increase the specific energy. The bad way to do it is to close the plate gap and add water, which increases the refining intensity. If fibre length is too short, verify if consistency is too high or low and adjust. If the consistency is good, then the plate gap is too small and must be increased.

Insights from Control Room Operator Manual (2 of 2)

(transcribed by Robert Harrison, April 2005)

In most cases, a variation in ML is due to a change in the density of the chips or of the wood species.

Weak B-A may be due to consistency being too low, or possibly damaged plates.

Variation in casing pressure is normally a consequence rather than a cause of operational instability.

A too-small plate gap in the flat section has a tendency to damage fibres quicker than in the conical section. The reason is that the flat zone operates at a lower consistency and therefore at a higher intensity. Metso recommends maintaining a gap in the flat section at least 0.2 mm larger than in the conical section.

Unstable ML can be caused by a problem with the feed and/or management of steam between the plates. The refiner will not be unstable if the feed is constant and the steam well evacuated:

- Primary:
  - Unstable steam in trémie tampon or pre-heater
  - Variable level or outlet feed rate from pre-heater
  - Worn plates, consistency too high…
- Secondary:
  - Unstable primary
  - Consistency too high

Four factors can affect pulp quality:

1. Consistency too high: Fibres become brittle and easier to break. They can also get overheated. This leads to shorter fibres and worse pulp.
2. Consistency too low: Fibre weight increases, and due to centrifugal force they spend less time between the plates. Response is to reduce the plate gap to maintain ML. Refining intensity increases since fibres spend less time between plates and therefore absorb more energy per impact.
3. Applied energy is too high, too low or unstable.
4. Lousy chips.

Primary freeness is a useful tool for guiding the choice of ML split between primary and secondary. A common split is 60/40.

Metso recommends waiting for a second (or even third) lousy PulpExpert reading before modifying the TMP operation *(means lag of 2-3 hours!)*

To avoid fibre breakage, Metso recommends operating at highest consistency and plate gap possible, while avoiding unstable operation or exceeding consistency of 65%.

APPENDIX IV:

Partial List of Variables Used in MVA Models and P&ID Locations

APPENDIX IV: Partial List of Variables Used in MVA Models

Tag	Description in PI Database
TMP REFINING LINE 1	
52SIC110.PV	PRODUC LIGNE 1 VIS 057 (production ligne 1, t/j)
52JIC139.AI	CHARGE RAFFINEUR 1 (cons. élect. raff. 1, "énergie appliquée", MW)
52JI189.AI	CHARGE RAFFINEUR 5 (cons. élect. raff. 5, "énergie appliquée", MW)
52FIC116.PV	DIL MP Z CEN R1 LX10T (dilution centrale raff. 1, L/min)
52FFC117.PV	DIL HP CYCL 1 LX10T (dilution cyclone raff. 1, L/min)
52FFC166.PV	DIL MP Z CEN R5 LX10T (dilution centrale raff. 5, L/min)
52FIC164.PV	DIL HP Z CON R5 LX10T (dilution conique, L/min)
52ZIC147.PV	POSIT PLAQUES V RAF 1 (position zone verticale raff. 1, mm)
52ZIC148.PV	POSIT PLAQUES H RAF 1 (position zone conique raff. 1, mm)
52ZIC197.PV	POSIT PLAQUES V RAF 5 (position zone verticale raff. 5, mm)
52ZIC198.PV	POSIT PLAQUES H RAF 5 (position zone conique raff. 5, mm)
52PCA111.PV	Pression boitier R1 (kPa)
52PIC105.PV	Pression alimentation R1 (kPa)
52PCA161.PV	Pression boitier R5 (kPa)
52PIC159.PV	Pression alimentation R5 (kPa)
52ni100.AI	Consistance calculée Raffineur 1 (%)
52ni150.AI	Consistance calculée Raffineur 5 (%)
53LIC011.PV	NIVEAU CU.DET.P531-401 (niveau cuve de détente 1, %)
52KQC139.AI	RAFF 1 VIE DES PLAQUES (h)
52KQC189.AI	RAFF 5 VIE DES PLAQUES (h)
TMP REFINING LINES 2, 3 & 4	
52SIC210.PV	PRODUC LIGNE PTM NO 2
52JIC239.AI	CHARGE RAFFINEUR 2

52FIC216.PV	DIL MP Z CEN R2 LX10T
52JI289.AI	CHARGE RAFFINEUR 6
52FFC217.PV	DIL HP CYCL 2 LX10T
52FFC266.PV	DIL MP Z CEN R6 LX10T
52FIC264.PV	DIL HP Z CON R6 LX10T
52SIC310.PV	PRODUC LIGNE PTM NO 3
52JIC339.AI	CHARGE RAFFINEUR 3
52FIC316.PV	DIL MP Z CEN R3 LX10T
52JI389.AI	CHARGE RAFFINEUR 7
52FFC317.PV	DIL HP CYCL 3 LX10T
52FFC366.PV	DIL MP Z CEN R7 LX10T
52FIC364.PV	DIL HP Z CON R7 LX10T
52SIC410.PV	PRODUC LIGNE PTM NO 4
52JIC439.AI	CHARGE RAFFINEUR 4
52FIC416.PV	DIL MP Z CEN R4 LX10T
52JI489.AI	CHARGE RAFFINEUR 8
52FFC417.PV	DIL HP CYCL 4 LX10T
52FFC466.PV	DIL MP Z CEN R8 LX10T
52FIC464.PV	DIL HP Z CON R8 LX10T
52KQC239.AI	RAFF 2 VIE DES PLAQUES
52KQC289.AI	RAFF 6 VIE DES PLAQUES
52KQC339.AI	RAFF 3 VIE DES PLAQUES
52KQC389.AI	RAFF 7 VIE DES PLAQUES
52KQC439.AI	RAFF 4 VIE DES PLAQUES
52KQC489.AI	RAFF 8 VIE DES PLAQUES
REJECT REFINING	
PTM_taux_rejets.cal	Calcule du taux de rejets
53JIC639.AI	CHARGE RAFFINEUR 9
53JIC689.AI	CHARGE RAFFINEUR 10
53KQC639.AI	RAFF 9 VIE DES PLAQUES
53KQC689.AI	RAFF10 VIE DES PLAQUES
PULP QUALITY	
Pex_L1_CSF	PulpExpert L1 CSF
Pex_L1_LMF	PulpExpert L1 LMF

Pex_L1_P200	PulpExpert L1 P200
Pex_L2_CSF	PulpExpert L2 CSF
Pex_L2_LMF	PulpExpert L2 LMF
Pex_L2_P200	PulpExpert L2 P200
Pex_L3_CSF	PulpExpert L3 CSF
Pex_L3_LMF	PulpExpert L3 LMF
Pex_L3_P200	PulpExpert L3 P200
Pex_L4_CSF	PulpExpert L4 CSF
Pex_L4_LMF	PulpExpert L4 LMF
Pex_L4_P200	PulpExpert L4 P200
Pex_AccTP_CSF	PulpExpert AccTP CSF
Pex_AccTP_LMF	PulpExpert AccTP LMF
Pex_AccTP_P200	PulpExpert AccTP P200
Pex_rej_CSF	PulpExpert rej CSF
Pex_rej_LMF	PulpExpert rej LMF
Pex_rej_P200	PulpExpert rej P200
Pex_alimFAD_CSF	PulpExpert alimFAD CSF
Pex_alimFAD_LMF	PulpExpert alimFAD LMF
Pex_alimFAD_P200	PulpExpert alimFAD P200
Pex_NivMP5_CSF	PulpExpert NivMP5 CSF
Pex_NivMP5_LMF	PulpExpert NivMP5 LMF
Pex_NivMP5_P200	PulpExpert NivMP5 P200
PAPER MACHINE 4	
MP4_Bob_Mere_Dechirure_SM.MOY	MP4 Bob Mere Dechirure SM.MOY
MP4_Bob_Mere_Dechirure_ST.MOY	MP4 Bob Mere Dechirure ST.MOY
MP4_Bob_Mere_eclatement.MOY	MP4 Bob Mere eclatement.MOY
MP4_Bob_Mere_Elong_SM.MOY	MP4 Bob Mere Elong SM.MOY
MP4_Bob_Mere_Elong_ST.MOY	MP4 Bob Mere Elong ST.MOY
MP4_Bob_Mere_Permeabilite.MOY	MP4 Bob Mere Permeabilite.MOY
MP4_Bob_Mere_Rupture_SM.MOY	MP4 Bob Mere Rupture SM.MOY
MP4_Bob_Mere_Rupture_ST.MOY	MP4 Bob Mere Rupture ST.MOY
MP4_Bob_Mere_TSI_SM.MOY	MP4 Bob Mere TSI SM.MOY
MP4_Bob_Mere_TSI_ST.MOY	MP4 Bob Mere TSI ST.MOY
MX4_CAL_Scan_Avg	MP4 épaisseur
MX4_BW_Scan_Avg	MP4 grammage

MX4_Bright_Scan_Avg	MP4 brillance
MP4_PELUCHAGE_DESSOUS	MP4_PELUCHAGE_DESSOUS
MP4_PELUCHAGE_DESSUS	MP4_PELUCHAGE_DESSUS
mp4-811-ffic-0104.pv	MP4 débit de cassé (L/min)
mx4_div_vit_calan_act	vitesse mp #4
STE_TESTPATE_CONS_EB_FOSSE_MP4.man	Consistance eau blanche fosse mp#4
PAPER MACHINE 5	
MP5_Bob_Mere_Dechirure_SM.MOY	MP5 Bob Mere Dechirure SM.MOY
MP5_Bob_Mere_Dechirure_ST.MOY	MP5 Bob Mere Dechirure ST.MOY
MP5_Bob_Mere_eclatement.MOY	MP5 Bob Mere eclatement.MOY
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MP5_Bob_Mere_Rupture_ST.MOY	MP5 Bob Mere Rupture ST.MOY
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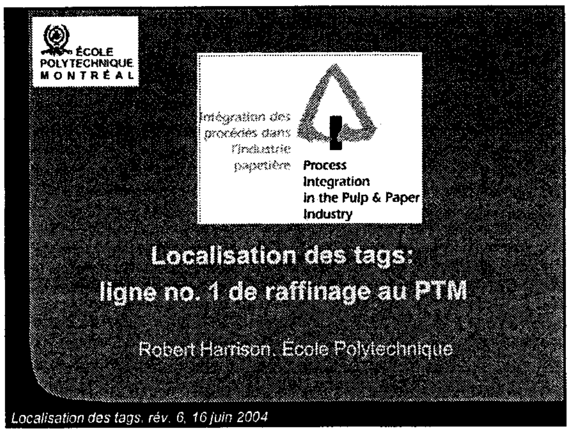
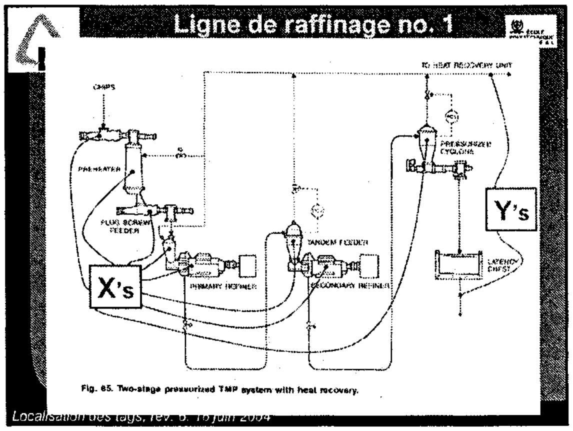
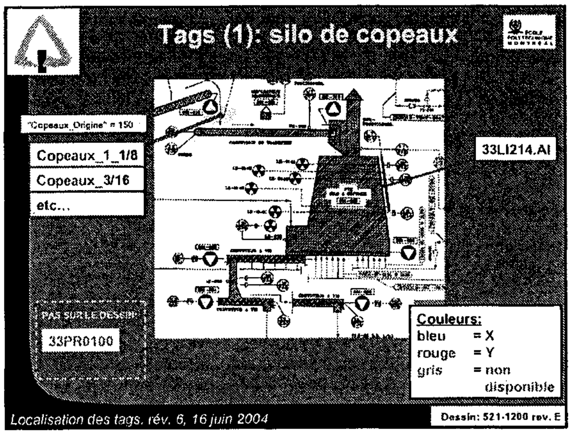
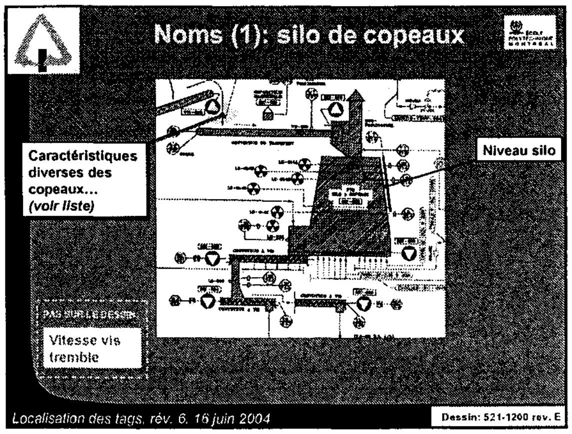
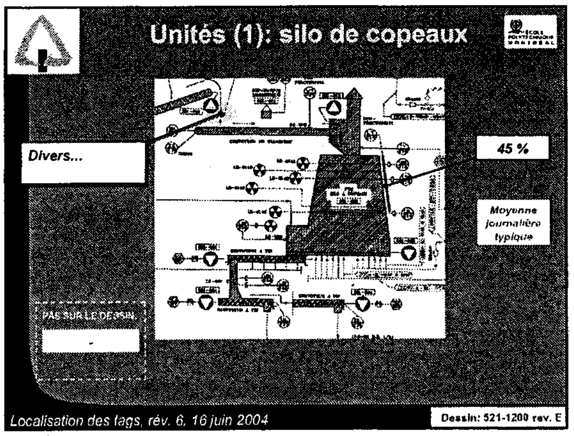
MP5_Bob_Mere_TSI_ST.MOY	MP5 Bob Mere TSI ST.MOY
MX5_CAL_Scan_Avg	MP5 épaisseur
MX5_BW_Scan_Avg	MP5 grammage
MX5_Bright_Scan_Avg	MP5 brillance
MP5_PELUCHAGE_DESSOUS	MP5_PELUCHAGE_DESSOUS
MP5_PELUCHAGE_DESSUS	MP5_PELUCHAGE_DESSUS
mp5-ffic-104.pv	MP5 débit de cassé (kL/min)
MX5_Div_Vit_Calan_Act	vitesse mp #5
STE_TESTPATE_CONS_EB_FOSSE_MP5.man	Consistance eau blanche fosse mp#5
HD TANK LEVELS	
53LR405.AI	NIVEAU TOTAL HD.1 A 4
53LR471.AI	NIVEAU RESERVOIR HD 1
53LR411.AI	NIVEAU RESERVOIR HD 2
53LR421.AI	NIVEAU RESERVOIR HD 3
53LR431.AI	NIVEAU RESERVOIR HD 4

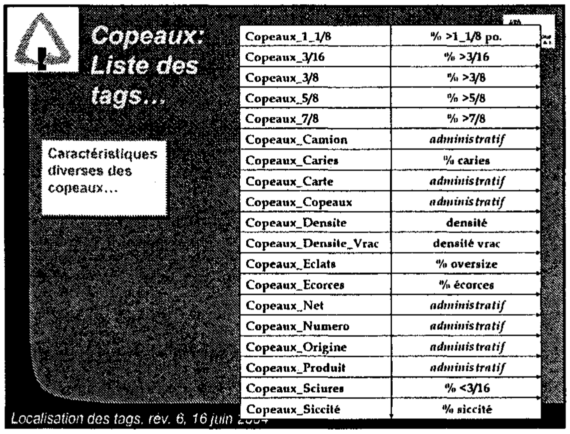




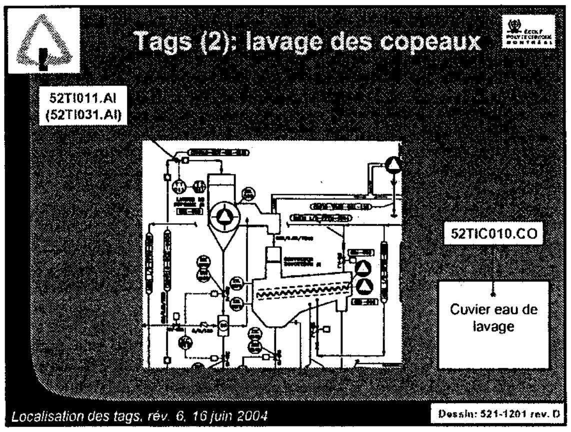


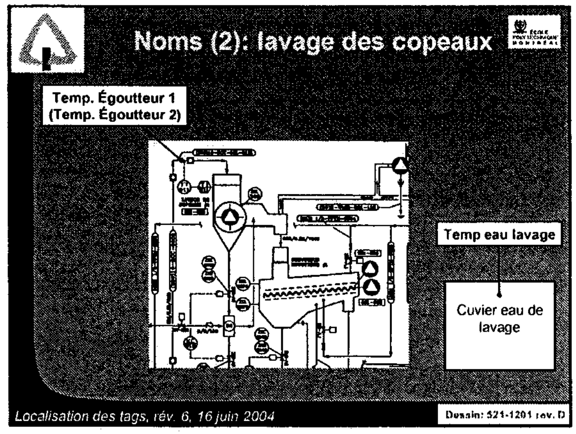


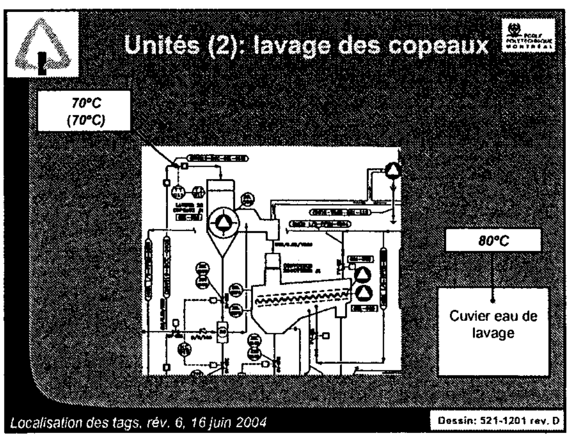


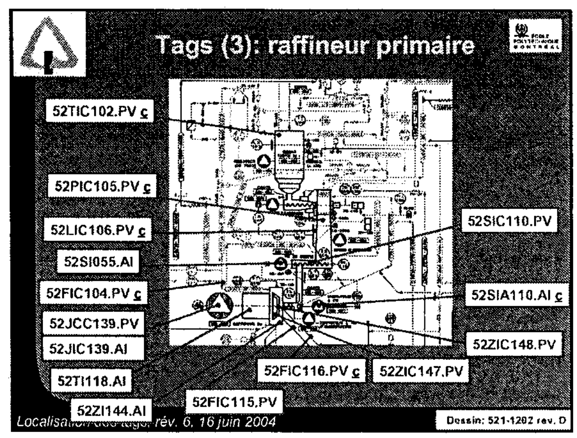


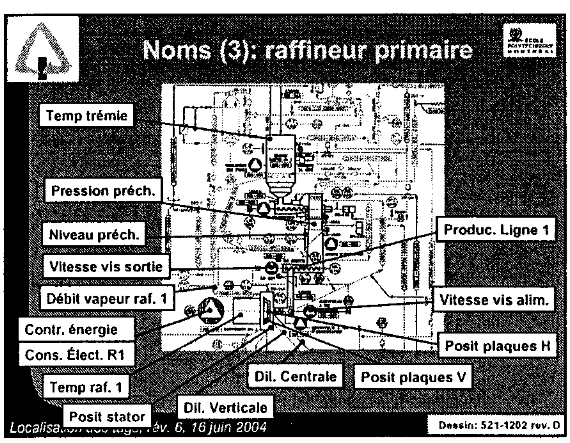
Copeaux_1_1/8	% >1_1/8 po.
Copeaux_3/16	% >3/16
Copeaux_3/8	% >3/8
Copeaux_5/8	% >5/8
Copeaux_7/8	% >7/8
Copeaux_Camion	*administratif*
Copeaux_Caries	% caries
Copeaux_Carte	*administratif*
Copeaux_Copeaux	*administratif*
Copeaux_Densite	densité
Copeaux_Densite_Vrac	densité vrac
Copeaux_Eclats	% oversize
Copeaux_Ecorces	% écorces
Copeaux_Net	*administratif*
Copeaux_Numero	*administratif*
Copeaux_Origine	*administratif*
Copeaux_Produit	*administratif*
Copeaux_Sciures	% <3/16
Copeaux_Siccité	% siccité

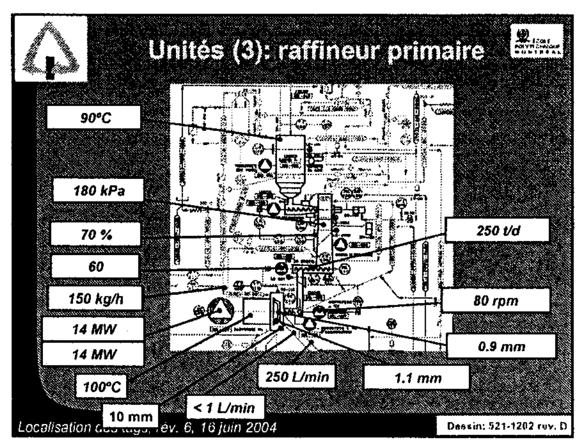

Tags (2): lavage des copeaux
52TI011.AI
(52TI031.AI)
52TIC010.CO
Cuvier eau de lavage
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 521-1201 rev. D

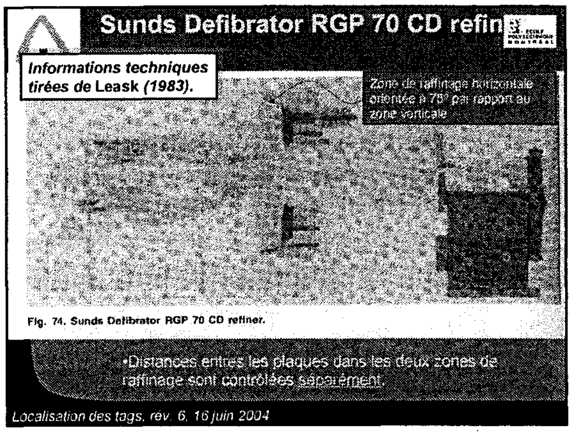

Noms (2): lavage des copeaux
Temp. Égoutteur 1
(Temp. Égoutteur 2)
Temp eau lavage
Cuvier eau de lavage
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 521-1201 rev. D

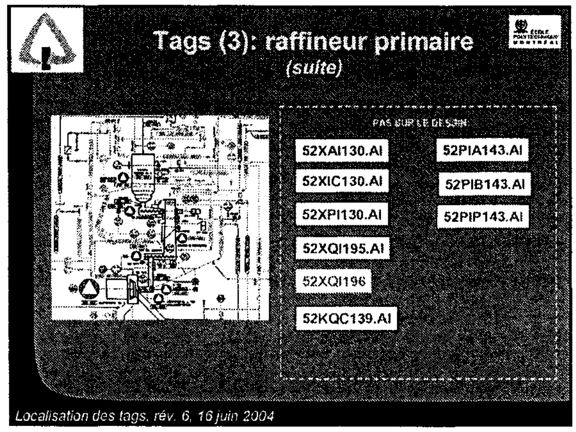

Unités (2): lavage des copeaux
70°C
(70°C)
80°C
Cuvier eau de lavage
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 521-1201 rev. D

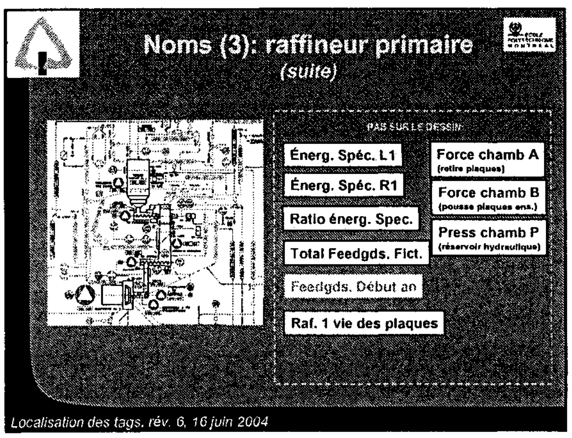

Tags (3): raffineur primaire
52TIC102.PV c
52PIC105.PV c
52LIC106.PV c
52SI055.AI
52FIC104.PV c
52JCC139.PV
52JIC139.AI
52TI118.AI
52ZI144.AI
52SIC110.PV
52SIA110.AI c
52ZIC148.PV
52FIC116.PV c
52ZIC147.PV
52FIC115.PV
rév. 6, 16 juin 2004
Dessin: 521-1202 rev. D

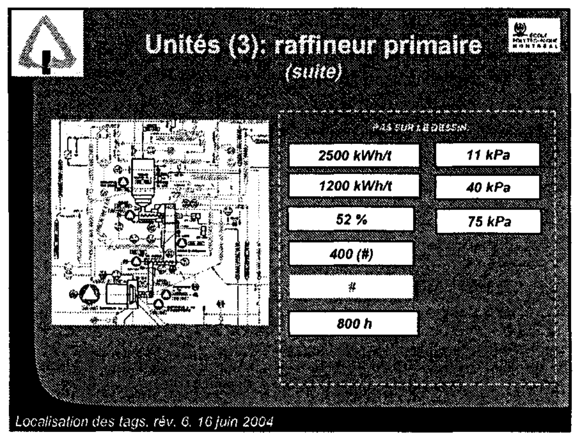

Noms (3): raffineur primaire
Temp trémie
Pression préch.
Niveau préch.
Vitesse vis sortie
Débit vapeur raf. 1
Contr. énergie
Cons. Élect. R1
Temp raf. 1
Posit stator
Produc. Ligne 1
Vitesse vis alim.
Posit plaques H
Dil. Centrale
Posit plaques V
Dil. Verticale
rév. 6, 16 juin 2004
Dessin: 521-1202 rev. D

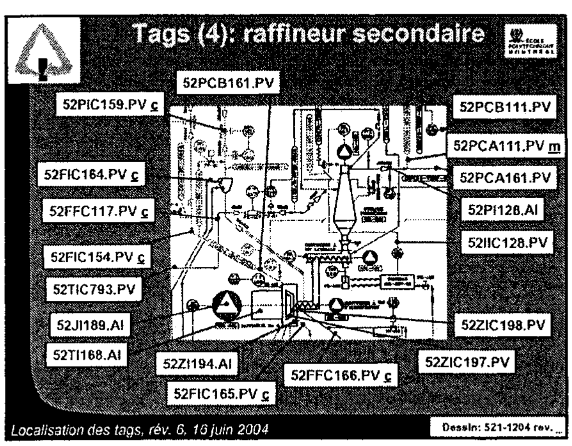

Unités (3): raffineur primaire
90°C
180 kPa
70 %
60
150 kg/h
14 MW
14 MW
100°C
10 mm
250 t/d
80 rpm
0.9 mm
250 L/min
1.1 mm
< 1 L/min
rév. 6, 16 juin 2004
Dessin: 521-1202 rev. D

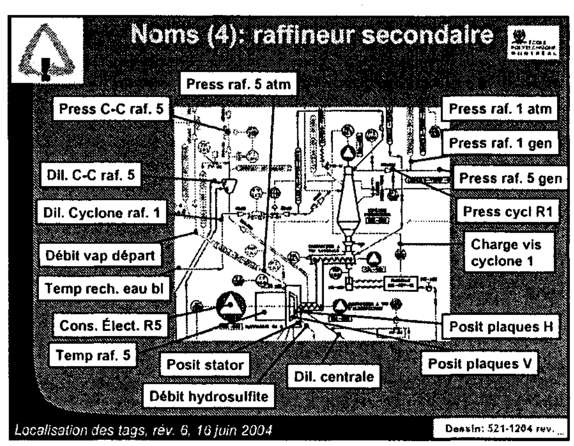

Sunds Defibrator RGP 70 CD refin
Informations techniques tirées de Leask (1983).
Zone de raffinage horizontale orientée à 75° par rapport au zone verticale
Fig. 74. Sunds Defibrator RGP 70 CD refiner.
•Distances entres les plaques dans les deux zones de raffinage sont contrôlées séparément.
Localisation des tags, rév. 6, 16 juin 2004

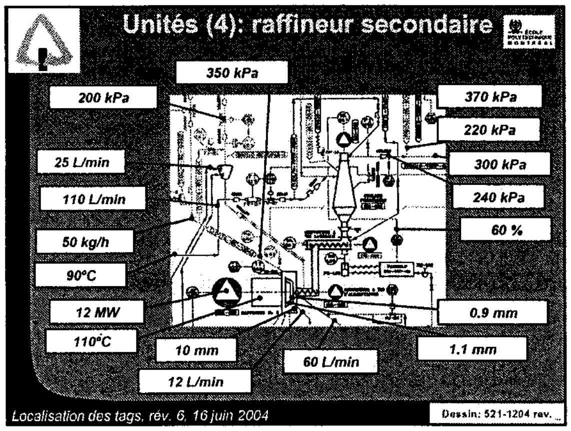

Tags (3): raffineur primaire
(suite)
PAS SUR LE DESSIN:
52XAI130.AI
52XIC130.AI
52XPI130.AI
52XQI195.AI
52XQI196
52KQC139.AI
52PIA143.AI
52PIB143.AI
52PIP143.AI
Localisation des tags, rév. 6, 16 juin 2004

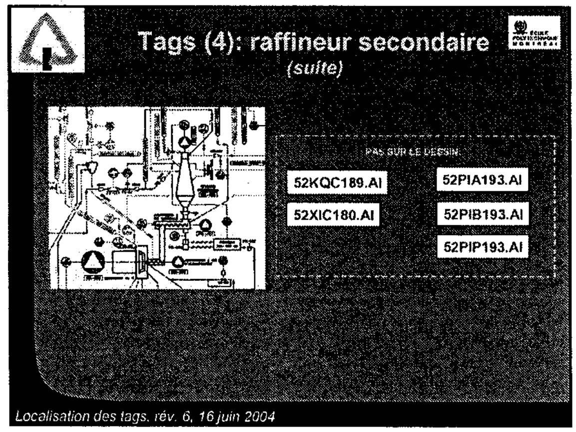

Noms (3): raffineur primaire
(suite)
PAS SUR LE DESSIN:
Énerg. Spéc. L1
Énerg. Spéc. R1
Ratio énerg. Spec.
Total Feedgds. Fict.
Feedgds. Début an
Raf. 1 vie des plaques
Force chamb A
(retire plaques)
Force chamb B
(pousse plaques ens.)
Press chamb P
(réservoir hydraulique)
Localisation des tags, rév. 6, 16 juin 2004

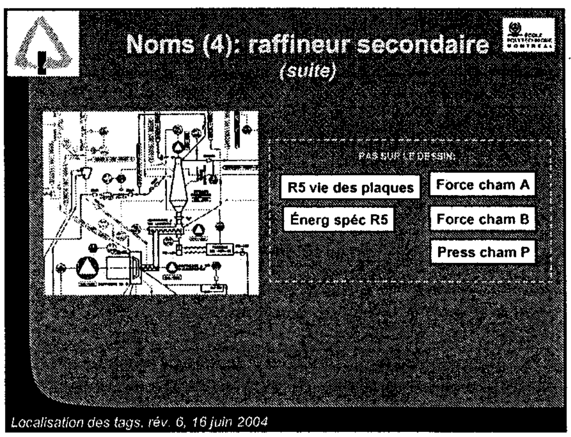

Unités (3): raffineur primaire
(suite)
PAS SUR LE DESSIN:
2500 kWh/t
1200 kWh/t
52 %
400 (#)
#
800 h
11 kPa
40 kPa
75 kPa
Localisation des tags, rév. 6, 16 juin 2004

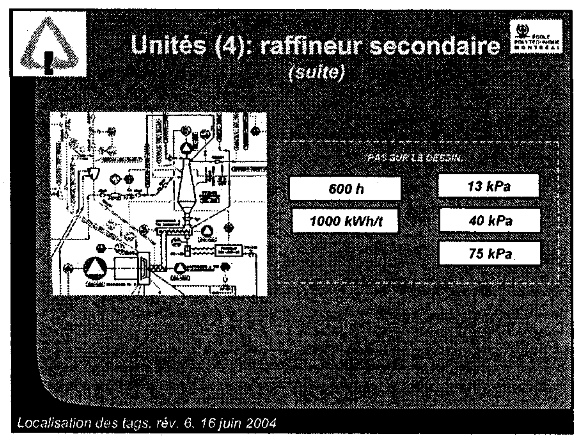

Tags (4): raffineur secondaire
52PCB161.PV
52PIC159.PV c
52FIC164.PV c
52FFC117.PV c
52FIC154.PV c
52TIC793.PV
52JI189.AI
52TI168.AI
52ZI194.AI
52FIC165.PV c
52FFC166.PV c
52ZIC197.PV
52ZIC198.PV
52PCB111.PV
52PCA111.PV m
52PCA161.PV
52PI128.AI
52IIC128.PV
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 521-1204 rev.

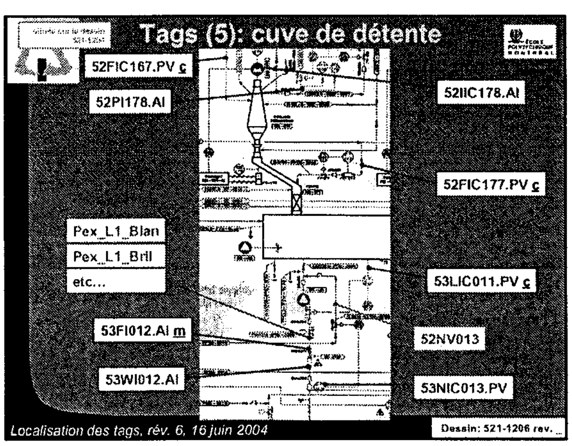

Noms (4): raffineur secondaire
Press raf. 5 atm
Press C-C raf. 5
Dil. C-C raf. 5
Dil. Cyclone raf. 1
Débit vap départ
Temp rech. eau bl
Cons. Élect. R5
Temp raf. 5
Posit stator
Débit hydrosulfite
Dil. centrale
Posit plaques V
Posit plaques H
Charge vis cyclone 1
Press cycl R1
Press raf. 5 gen
Press raf. 1 gen
Press raf. 1 atm
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 521-1204 rev.

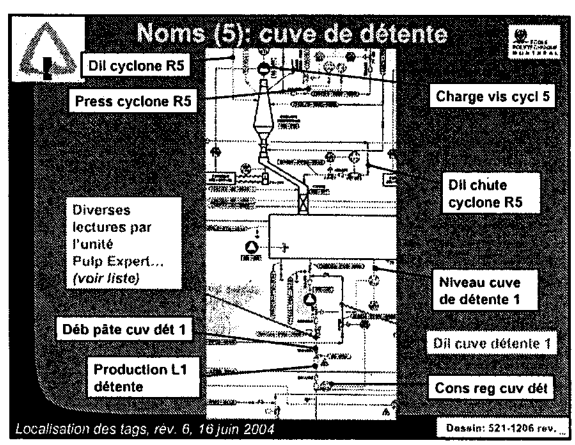

Unités (4): raffineur secondaire
350 kPa
200 kPa
370 kPa
220 kPa
25 L/min
300 kPa
110 L/min
240 kPa
60 %
50 kg/h
90°C
12 MW
0.9 mm
110°C
10 mm
60 L/min
1.1 mm
12 L/min
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 521-1204 rev.

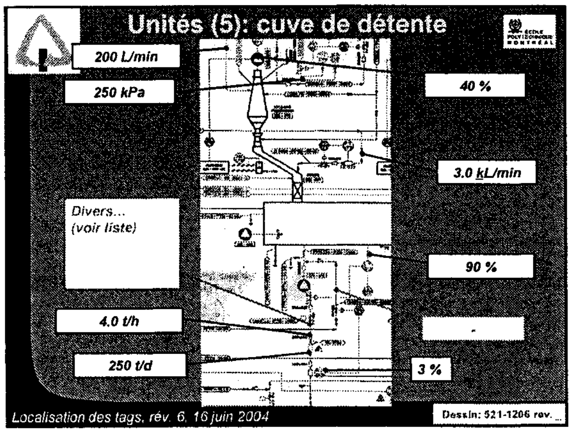

Tags (4): raffineur secondaire
(suite)
PAS SUR LE DESSIN:
52KQC189.AI
52PIA193.AI
52XIC180.AI
52PIB193.AI
52PIP193.AI
Localisation des tags, rév. 6, 16 juin 2004

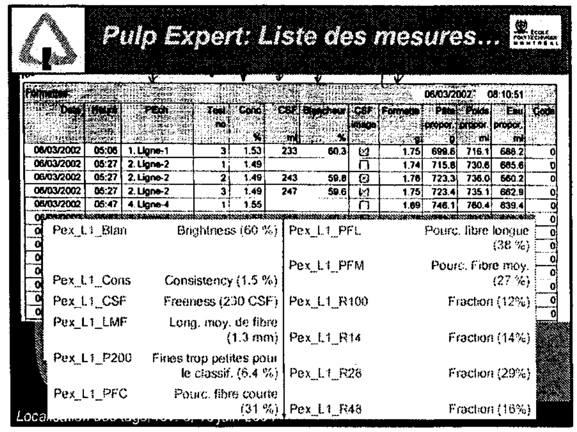

Noms (4): raffineur secondaire
(suite)
PAS SUR LE DESSIN:
R5 vie des plaques
Force cham A
Énerg spéc R5
Force cham B
Press cham P
Localisation des tags, rév. 6, 16 juin 2004

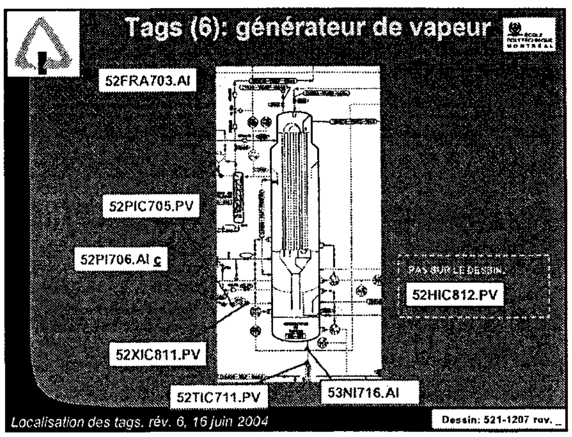

Unités (4): raffineur secondaire
(suite)
PAS SUR LE DESSIN:
600 h
13 kPa
1000 kWh/t
40 kPa
75 kPa
Localisation des tags, rév. 6, 16 juin 2004

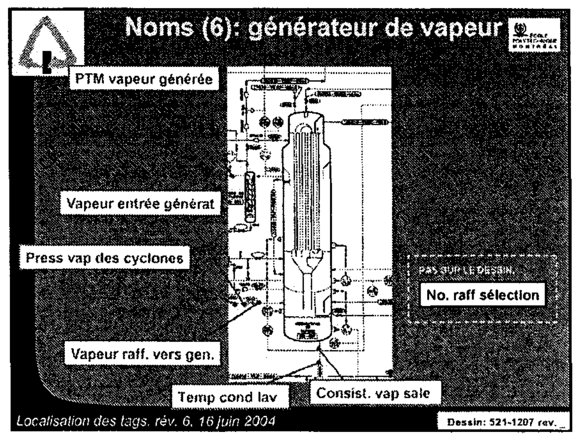

Tags (5): cuve de détente
52FIC167.PV c
52PI178.AI
52IIC178.AI
52FIC177.PV c
Pex_L1_Blan
Pex_L1_Bril
etc...
53LIC011.PV c
53FI012.AI m
52NV013
53WI012.AI
53NIC013.PV
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 521-1206 rev.

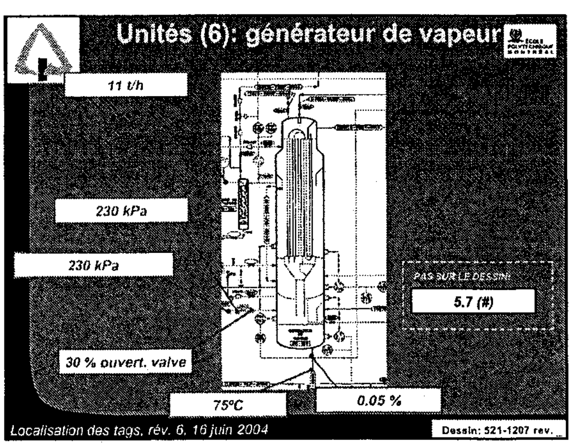

Noms (5): cuve de détente
Dil cyclone R5
Press cyclone R5
Charge vis cycl 5
Dil chute cyclone R5
Diverses lectures par l'unité Pulp Expert... (voir liste)
Niveau cuve de détente 1
Déb pâte cuv dét 1
Dil cuve détente 1
Production L1 détente
Cons reg cuv dét
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 521-1206 rev.

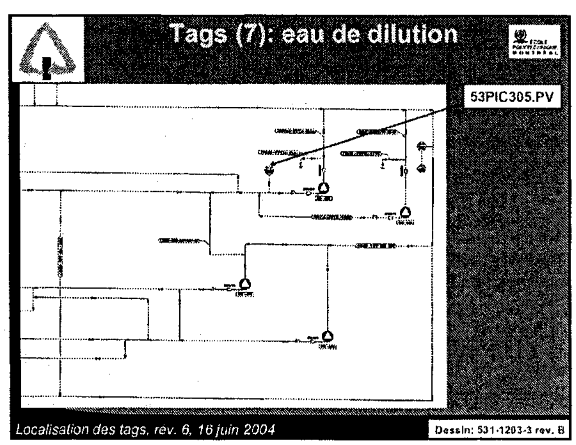

Unités (5): cuve de détente
200 L/min
250 kPa
40 %
3.0 kL/min
Divers...
(voir liste)
90 %
4.0 t/h
250 t/d
3 %
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 521-1206 rev. _

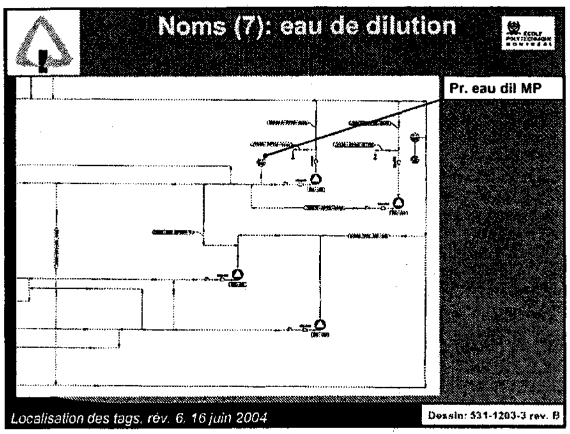

Pulp Expert: Liste des mesures...
Pex_L1_Blan
Brightness (60 %)
Pex_L1_PFL
Pourc. fibre longue (38 %)
Pex_L1_PFM
Pourc. Fibre moy. (27 %)
Pex_L1_Cons
Consistency (1.5 %)
Pex_L1_CSF
Freeness (230 CSF)
Pex_L1_R100
Fraction (12%)
Pex_L1_LMF
Long. moy. de fibre (1.3 mm)
Pex_L1_R14
Fraction (14%)
Pex_L1_P200
Fines trop petites pour le classif. (6.4 %)
Pex_L1_R28
Fraction (29%)
Pex_L1_PFC
Pourc. fibre courte (31 %)
Pex_L1_R48
Fraction (16%)

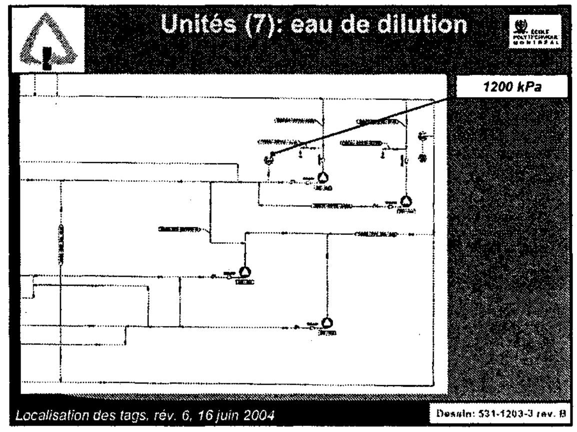

Tags (6): générateur de vapeur
52FRA703.AI
52PIC705.PV
52PI706.AI c
PAS SUR LE DESSIN:
52HIC812.PV
52XIC811.PV
52TIC711.PV
53NI716.AI
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 521-1207 rev. _

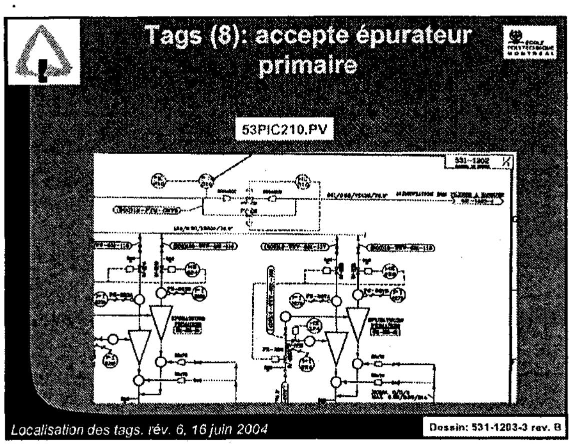

Noms (6): générateur de vapeur
PTM vapeur générée
Vapeur entrée générat
Press vap des cyclones
PAS SUR LE DESSIN:
No. raff sélection
Vapeur raff. vers gen.
Temp cond lav
Consist. vap sale
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 521-1207 rev. _

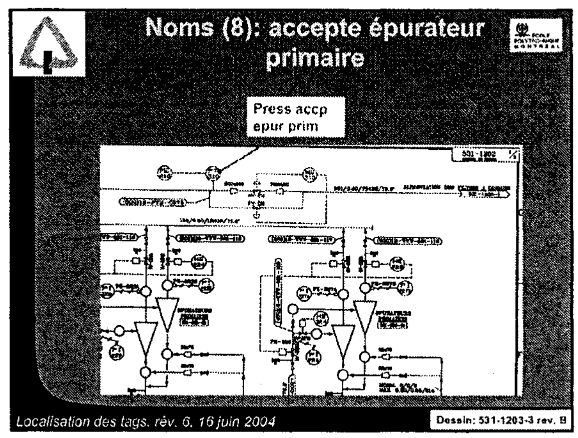

Unités (6): générateur de vapeur
11 t/h
230 kPa
230 kPa
PAS SUR LE DESSIN:
5.7 (#)
30 % ouvert. valve
75°C
0.05 %
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 521-1207 rev. _

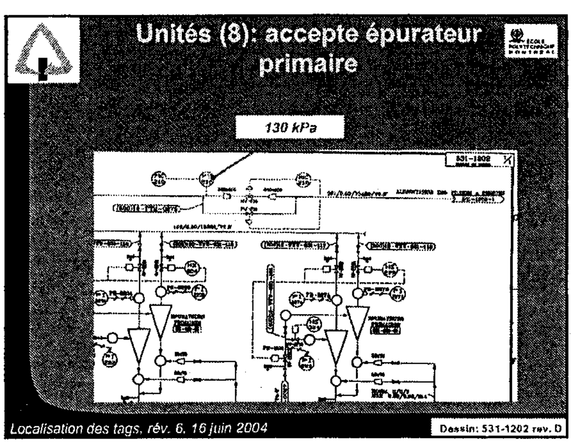

Tags (7): eau de dilution
53PIC305.PV
Localisation des tags, rev. 6, 16 juin 2004
Dessin: 531-1203-3 rev. B

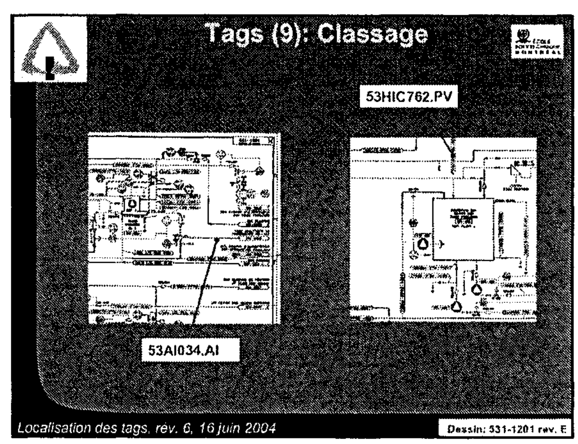

Noms (7): eau de dilution
Pr. eau dil MP
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1203-3 rev. B

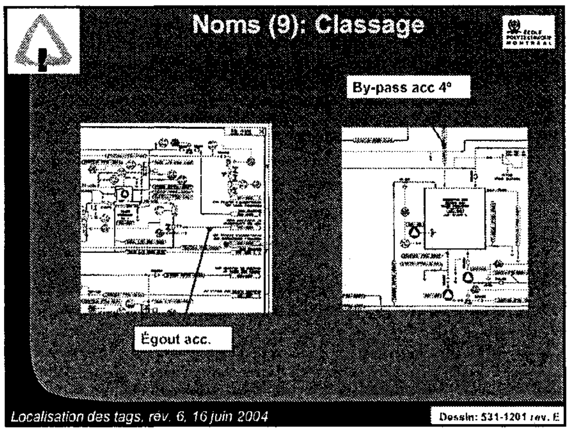

Unités (7): eau de dilution
1200 kPa
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1203-3 rev. B

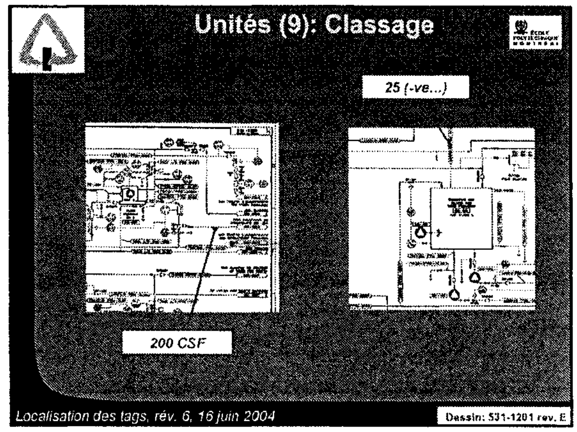

Tags (8): accepte épurateur primaire
53PIC210.PV
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1203-3 rev. B

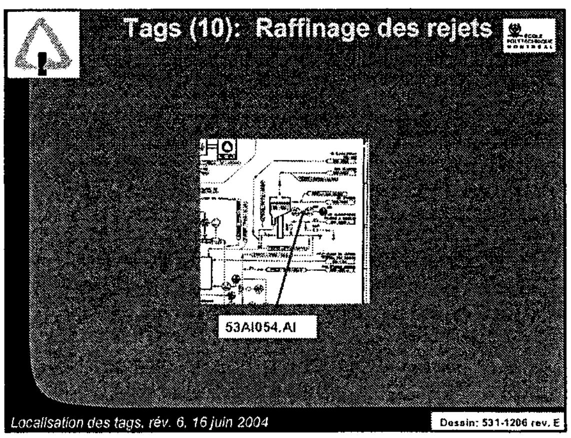

Noms (8): accepte épurateur primaire
Press accp epur prim
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1203-3 rev. B

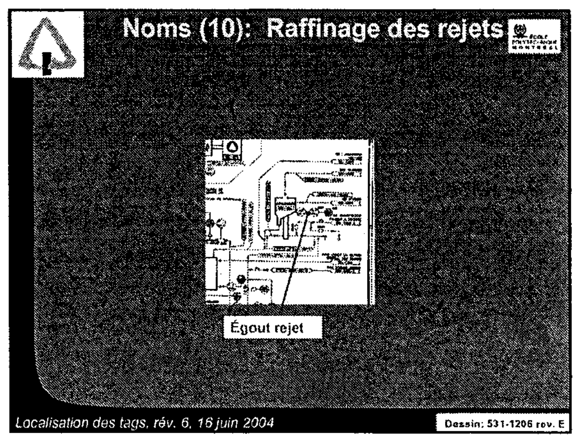

Unités (8): accepte épurateur primaire
130 kPa
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1202 rev. D

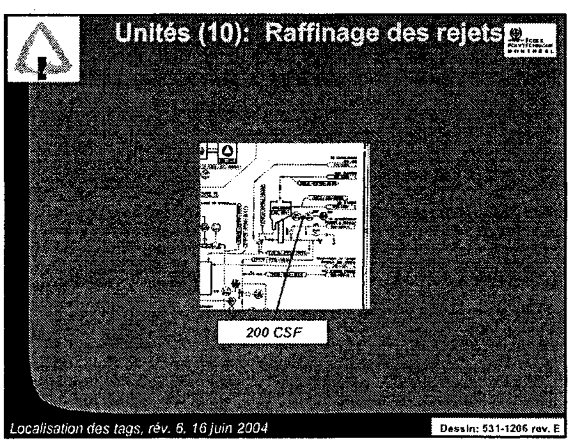

Tags (9): Classage
53HIC762.PV
53AI034.AI
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1201 rev. E

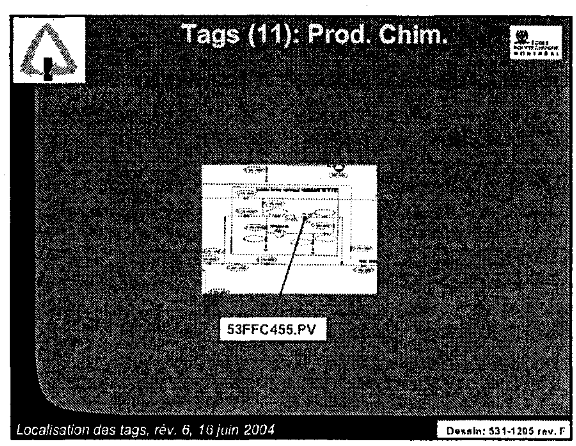

Noms (9): Classage
By-pass acc 4°
Égout acc.
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1201 rev. E

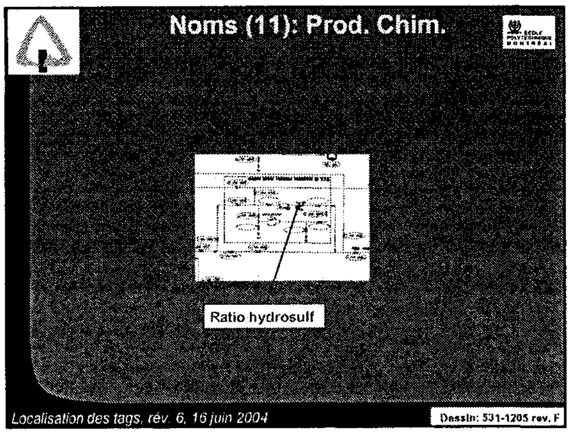

Unités (9): Classage
25 (-ve...)
200 CSF
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1201 rev. E

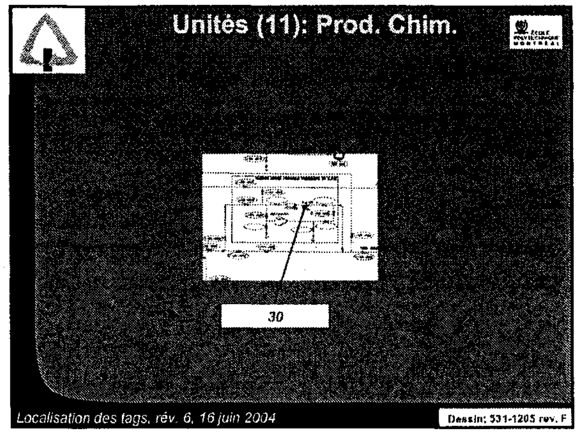

Tags (10): Raffinage des rejets
53AI054.AI
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1206 rev. E

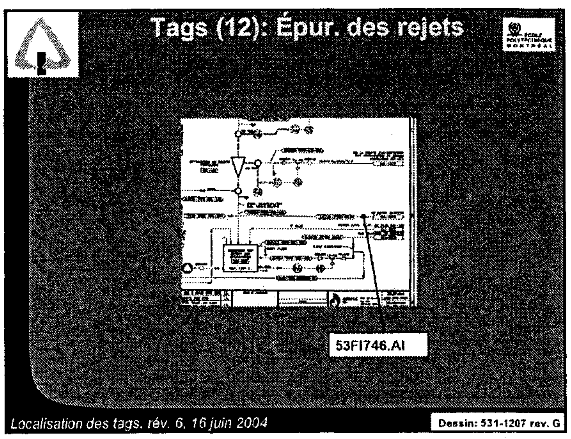

Noms (10): Raffinage des rejets
Égout rejet
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1206 rev. E

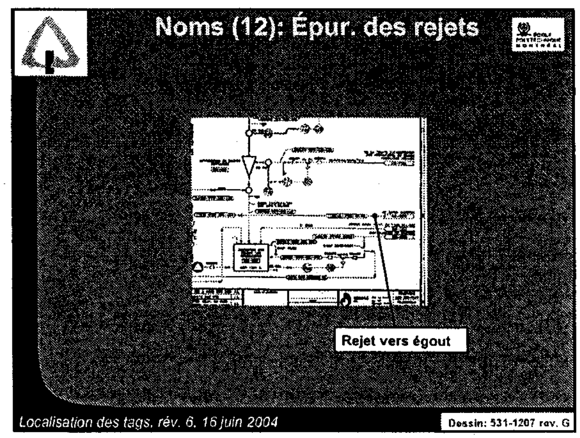

Unités (10): Raffinage des rejets
200 CSF
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1206 rev. E

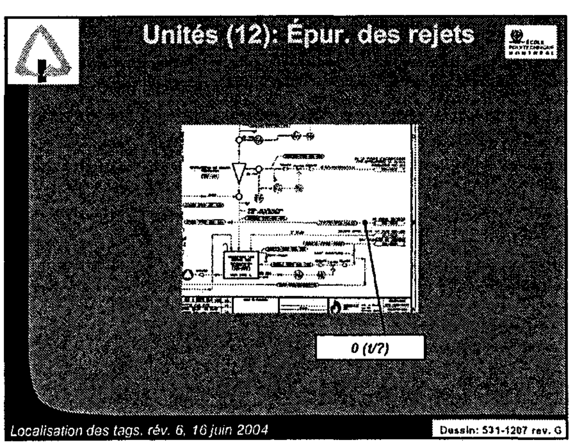

Tags (11): Prod. Chim.
53FFC455.PV
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1205 rev. F

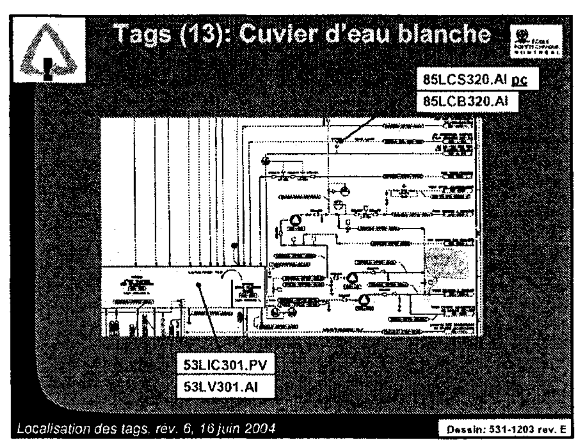

Noms (11): Prod. Chim.
Ratio hydrosulf
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1205 rev. F

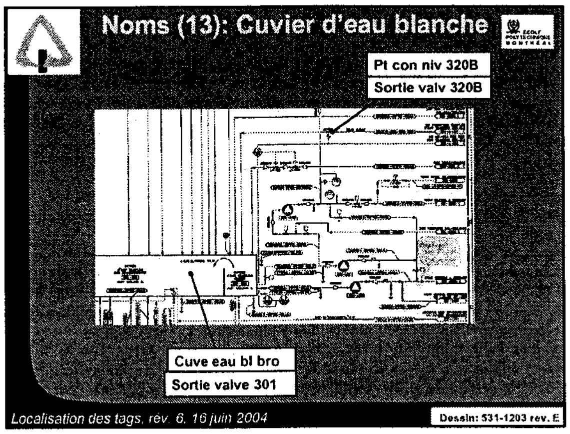

Unités (11): Prod. Chim.
30
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1205 rev. F

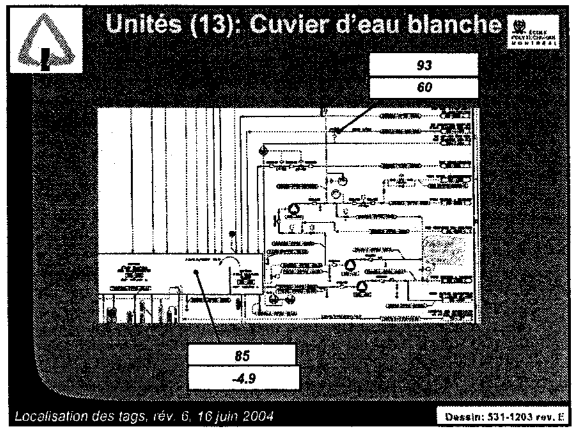

Tags (12): Épur. des rejets
53FI746.AI
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1207 rev. G

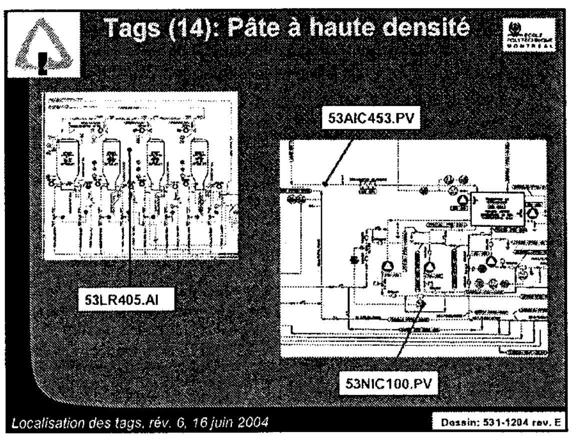

Noms (12): Épur. des rejets
Rejet vers égout
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1207 rev. G

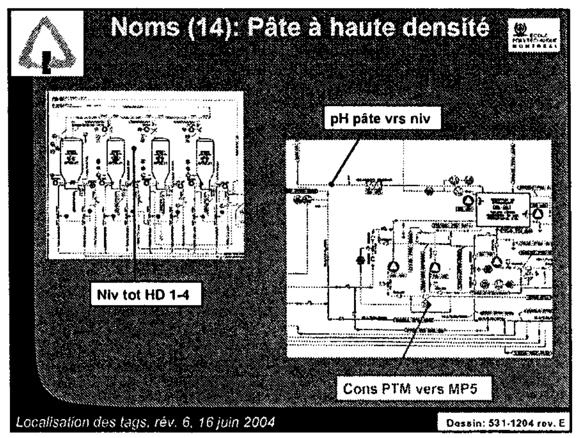

Unités (12): Épur. des rejets
0 (l/?)
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1207 rev. G

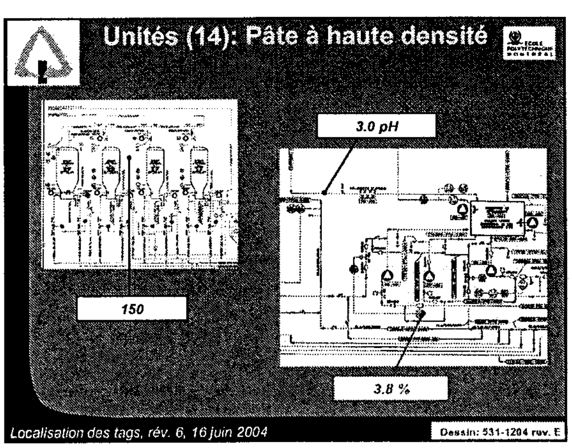

Tags (13): Cuvier d'eau blanche
85LCS320.AI pc
85LCB320.AI
53LIC301.PV
53LV301.AI
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1203 rev. E

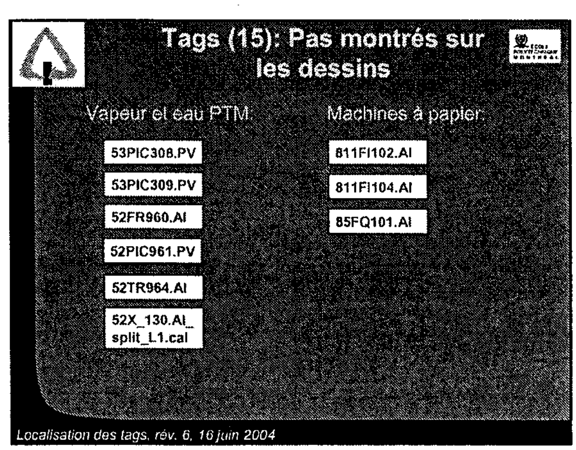

Noms (13): Cuvier d'eau blanche
Pt con niv 320B
Sortie valv 320B
Cuve eau bl bro
Sortie valve 301
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1203 rev. E

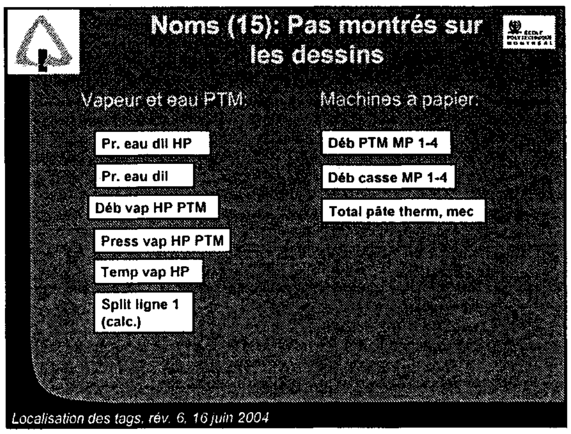

Unités (13): Cuvier d'eau blanche
93
60
85
-4.9
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1203 rev. E

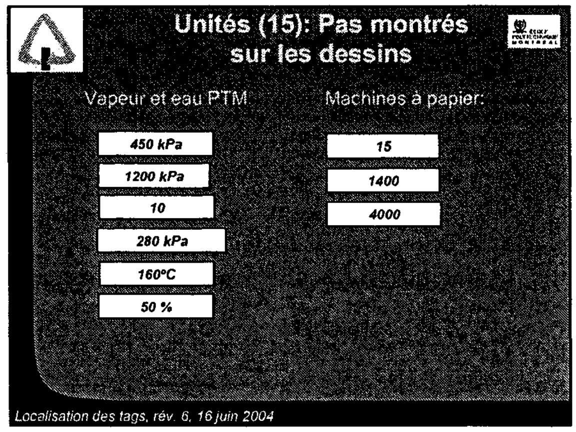

Tags (14): Pâte à haute densité
53AIC453.PV
53LR405.AI
53NIC100.PV
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1204 rev. E


Noms (14): Pâte à haute densité
pH pâte vrs niv
Niv tot HD 1-4
Cons PTM vers MP5
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1204 rev. E


Unités (14): Pâte à haute densité
3.0 pH
150
3.8 %
Localisation des tags, rév. 6, 16 juin 2004
Dessin: 531-1204 rev. E


Tags (15): Pas montrés sur les dessins
Vapeur et eau PTM:
53PIC308.PV
53PIC309.PV
52FR960.AI
52PIC961.PV
52TR964.AI
52X_130.AI_split_L1.cal
Machines à papier:
811FI102.AI
811FI104.AI
85FQ101.AI
Localisation des tags, rév. 6, 16 juin 2004


Noms (15): Pas montrés sur les dessins
Vapeur et eau PTM:
Pr. eau dil HP
Pr. eau dil
Déb vap HP PTM
Press vap HP PTM
Temp vap HP
Split ligne 1 (calc.)
Machines à papier:
Déb PTM MP 1-4
Déb casse MP 1-4
Total pâte therm, mec
Localisation des tags, rév. 6, 16 juin 2004


Unités (15): Pas montrés sur les dessins
Vapeur et eau PTM
450 kPa
1200 kPa
10
280 kPa
160°C
50 %
Machines à papier:
15
1400
4000
Localisation des tags, rév. 6, 16 juin 2004

APPENDIX V:

International Peer-Reviewed Publication – 2004 – Pulp and Paper Canada

MULTIVARIATE ANALYSIS OF REFINER OPERATING DATA FROM A TMP NEWSPRINT MILL

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BSTRACT

Process values upstream and downstream of the primary nd secondary refiners at a TMP newsprint mill were obtained or 34 consecutive months. Two types of multivariate analysis ere performed on daily averages, Principal Component nalysis (PCA) and Projection to Latent Surfaces (PLS), sing different combinations of variables. Although tatistically significant models were obtained from the mill ata, it is seems that the available chip data do not tell the hole story. Also, pulp throughput dominated the results even ithin a relatively narrow range of normal production rates. Nevertheless, it was possible to make a reasonable first ttempt at a possible physical interpretation of the model omponents.

NTRODUCTION

Many external factors such as seasonal variations and hanges in incoming chip quality are beyond the control of the MP mill operator. These could conceivably be compensated hrough controllable internal factors, but key pulp haracteristics which could serve as quality targets are not lways measured directly.

One option is to model in real time parameters that annot be measured continuously, in order to apply inferential ontrol ("soft sensor") as reported in Strand [1] and lsewhere [2, 3]. Before proposing any such control strategy, owever, it is necessary to understand the correlations and rends which are inherent to the refining operation using istorical data.

The TMP newsprint mill under investigation has had a igh-speed PI data historian in place for 34 months, into which irtually all process and operating data for the entire mill are ed. The mill has over 6 000 data tags, some of which are pdated every 10 seconds, potentially representing millions of alues per day.

The resulting data explosion has created a daunting mass f information, one for which the automated pattern-ecognition techniques of multivariate analysis (MVA) are erfectly suited. Mill personnel have tried to establish elationships between the process variables by considering nly a few at a time, an impossible task, hence their interest in o-operating with École Polytechnique on a new approach.

Previous papers applying MVA to paper production have hown that dozens or even hundreds of process parameters can e boiled down to a mere handful of underlying "latent ariables", corresponding to unmeasured fundamental haracteristics of the system [1, 4, 5, 6, 7, 8]. Using data from he refiner section of a TMP newsprint mill, Browne [9] found hat a portion of the variability in the pulp properties could be xplained by two latent variables: the first related to wood reshness, as measured by the potential brightness of the wood; and the second to the ease with which energy could be applied to the wood, typically higher in summer.

The primary purpose of this paper is to perform MVA on daily average process data at this mill, to determine how many latent variables are required to adequately describe the refining section.

METHODOLOGY

One of the mill's four pulp production lines was selected for study. Using the process and instrumentation diagrams, key data tags were identified on and around the primary and secondary refiners, including:

- Chip quality data (grab samples at the TMP feed conveyor, analysed in a laboratory): chip size distribution, bulk density, humidity.
- Refiner operating data, such as: throughput; specific energy imparted to the chips; energy split between the primary and secondary refiner; vertical and conical plate distances; dilution rates; levels, pressures and temperatures in various units immediately connected to the refiners; steam generation rate; voltage at chip screw conveyors; specific hydrosulphite consumption.
- Equipment data, such as: operational hours elapsed since refiner plates were last replaced; number of refiners sending steam to heat recovery at any given moment; number of "feedguard" events indicating refiner blockages; refiner body temperature.
- Pulp quality data in the Line 1 latency chest (automated, on-line analysis of grab samples using Pulp Expert system): fibre length distribution; freeness; consistency; brightness.
- Season, represented by the average monthly temperature measured at a nearby Environment Canada meteorological station.

In all, some 110 data tags were included in the study. Daily means were extracted for the full 34 months, viz., November 23rd, 1999, to October 1st, 2002. Other time scales were investigated (1-hour, 8-hour) as well as alternative averaging techniques (medians), but for this initial effort daily averages offered the advantage of simplicity and comparability to previous authors.

Different runs were devised, some using fewer variables to allow comparison with previous authors. Other runs were planned using all the available variables, to test the limits of the MVA technique, which like any statistical method generally benefits from having a large number of data points.

The first step for each run was to perform Principal Component Analysis (PCA) on the entire dataset, normalised to mean of 0 and variance of 1, to identify outliers and obtain an overall picture. Periods of unusually low production (< 100 t/d) were excluded beforehand, as previous experience had shown that these systematically produce major outliers.

Partial Least Squares (PLS) analysis, a form of multivariate regression, was performed using two medium fibre length fractions as the Y set, and upstream data as the X set.

CHARACTERISTICS OF INCOMING CHIPS

The mill has a maximum two-day chip pile inventory, such that there is little or no buffering of incoming chip variability. During the 34 month period under study, chips came from a variety of outside suppliers, and often the exact source and species were unknown.

Chip characteristics are measured on grab samples from every incoming truck shipment, and on instantaneous grab samples taken every 8 hours at the TMP feed conveyor which feeds all four refining lines. Size distribution is measured with ι Gradex unit at the chip receiving lab; other parameters are neasured manually.

PCA on the TMP feed conveyor data yielded a combined ₹^{2} of 37% and Q^2 of 20%. The latter is the predictive power)f the model, calculated by systematically removing a portion)f the dataset and comparing to the model obtained from the emaining data.

For the chip data, there was only one principal :omponent, very strongly correlated with season:

- Higher in summer: chips longer than 5/8 in.
- Higher in winter: chips shorter than 3/8 in.; chip density; chip moisture.

These trends were already apparent from the raw data, ınd make sense physically; the interesting point is the lack of ıny other components, indicating no other statistically ignificant correlations between the chip properties. This may ›e partly due to the sparseness of the data, with only 3 grab amples per day.

Note that chip brightness was not measured. Little or no nformation was available on the wood species, freshness of he wood, the age of the tree, chipper type or other factors vhich can impact on final pulp quality [8, 10]. This may ccount for the low predictive power of the model.

'INAL PAPER QUALITY

Final paper quality is of paramount importance to the nill, and can be influenced by many factors. In particular, ;altin [6] found that fibre length is a critical factor to tear trength.

This conclusion was supported by PCA analysis of ourly data from the mill, taken during a typical week in ;eptember 2002 when the chip supply was relatively constant. Comparison of pulp quality variables and newsprint quality ariables showed that the proportion of medium sized fibres /as strongly correlated with important paper characteristics uch as permeability, stretch, burst strength and tear strength.

Based on these results, the R28 and R48 fibre length :actions were retained as the Y set for PLS analysis at the efiner section. Note that no daily pulp handsheet test data /ere available for the individual refining lines during the 34-ıonth period.

CA ON SELECTED REFINER OPERATING DATA

An initial PCA was performed using only fourteen of the 10 available variables, to gain insight into the overall process ;ee Table I). The list was based on one used in a previous :udy [9].

The PCA yielded two principal components, with a ›mbined R^2 of 44% and Q^2 of 24%. There were no major utliers, so all data points were retained in the model.

TABLE I: VARIABLES USED IN INITIAL PCA

SEASON	Avg. monthly outdoor temp. 123
52FIC165.P	Hydrosulfite consumption (L/m)
52XAI130.A	Specific energy – Line 1 (kWh/t)
Pex_L1_Bla	Brightness at No. 1 Latency Chest
Pex_L1_Con	Consistency at No. 1 Latency Chest (Log)
Pex_L1_CSF	Freeness at No. 1 Latency Chest
Pex_L1_LMF	Avg. Fibre Length at No. 1 Latency Chest
Pex_L1_P200	Fines Fraction at No. 1 Latency Chest
Pex_L1_R100	R100 Fraction at No. 1 Latency Chest
Pex_L1_R14	R14 Fraction at No. 1 Latency Chest
Pex_L1_R28	R28 Fraction at No. 1 Latency Chest
Pex_L1_R48	R48 Fraction at No. 1 Latency Chest
CopDENS	Chip Density at TMP Feed Conveyor
CopSICC	Chip % Solids at TMP Feed Conveyor

Figure 1 is a score plot of the observations, in this case daily averages. The ellipse indicates the 95% confidence limit. The first component was strongly correlated with the time of year, both in terms of average outdoor temperature and calendar seasons, with some segregation between the three different years under study. This component was also strongly correlated with bleach consumption (higher in winter) and pulp brightness (higher in summer). It therefore appears that this component may be related to wood freshness, as reported by Browne [9]. The outliers in the top-right corner correspond to observations with higher fines and lower long-fibre fractions.

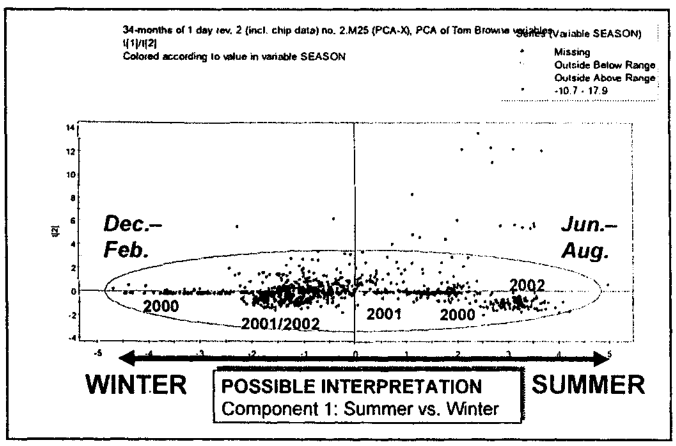
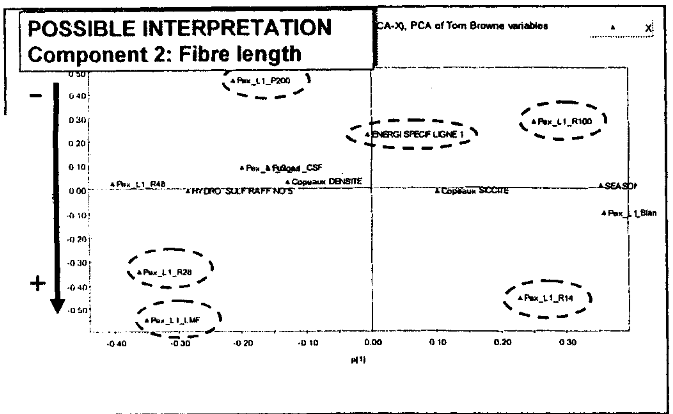


Fig. 1. Score Plot of 34-month Refiner Data with 14 Tags

Figure 2 is the corresponding loadings plot, showing how the variables correlate with respect to the same first two components. The second component was dominated by fines fraction and fibre length, and to a lesser extent with Line 1 specific energy (these variables are in the dashed circles). As no handsheet testing data were available, it is not possible to relate this directly with strength properties, and so it is difficult to conclude whether this corresponds to the second component reported by Browne [9], despite the obvious similarities.



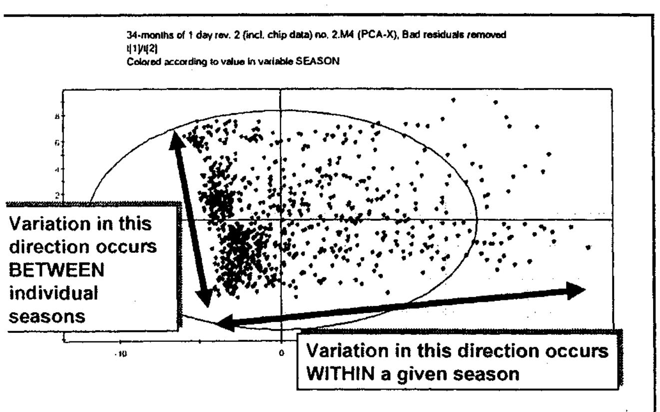
ʼig. 2. Loadings Plot with 14 Tags

›CA ON ENTIRE REFINER DATA SET

The inclusion of all 110 tags led to a PCA with several najor outliers, all of which were associated with periods of ow production. When all data points with a production level ›elow 150 t/d were removed, these outliers disappeared. ncidentally, the study of low production days may merit eparate investigation in the future, as these correspond tart-up and shut-down days.

The final PCA yielded four principal components, with a ombined R^2 of 44%, roughly the same as the previous case. ʼhe Q^2 value is much improved, however at 37%. This means hat the model fit is about the same as before, but the ›redictive power is much better when using a large number of ariables. This could be an advantage when creating a soft ensor, in order to give the controller the best chance of uccess.

The score plot shown in Figure 3 shows the relationship etween the first two components and time. Individual bservations vary both between seasons and within a given eason. Further investigation revealed that the individual easons were segregated, for instance, the winters of 2000, 001 and 2002.



ig. 3. Score Plot of 34-month Refiner Data with 110 Tags

The loadings plot in Figure 4 shows a possible terpretation of these same first two components. Even ough the low production points had previously been moved, pulp throughput continued to dominate the PCA sults. This is probably due to the large number of variables at change when the throughput changes, such as dilution ›ws, screw feeder motor voltages and so forth. It may be ›cessary in the future to give these variables a lesser weighting in the model (at present all variables have been given equal weighting).

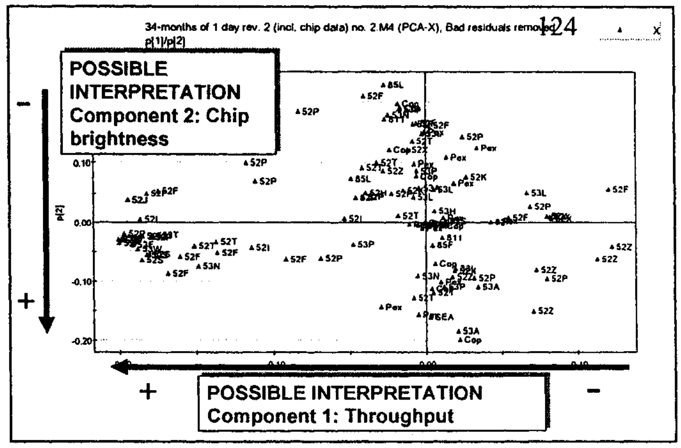


Fig. 4. Loadings Plot with 110 Tags

The second and third components are very similar to the two found earlier using the short list of 14 variables, although it is difficult to say with certainty if they are the same. The fourth component is less obvious, but appears to be related to refiner plate gap. All these possible interpretations would have to be verified either experimentally or through further investigation.

PLS ON MEDIUM-FIBRE-LENGTH FRACTIONS

The complete list of variables was again used in performing PLS analysis, with R28 and R48 for Y's. All other response variables were excluded. Three components were found, with a combined R^2 of 43% and Q^2 of 40%. The PCA results for the remaining ninety-odd X variables strongly resembled those for the entire dataset.

The "variable importance plot" in Figure 5 ranks the different X's in terms of prominence in modelling the Y's. The first bar on the left, representing season, clearly dominates, followed by two other parameters: dilution water pressure and primary refiner plate position. The rest tend to decline in importance gradually, probably due to the very high degree of correlation between the X's.

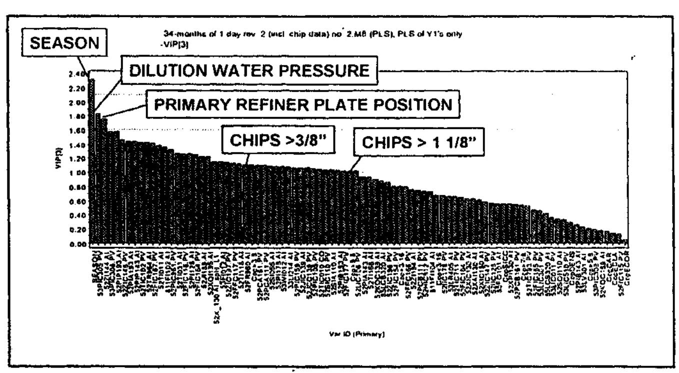


Fig. 5. Variable Importance Plot of PLS Model

In spite of the strong seasonal variability in the chip size, the different chip size fractions are not very prominent among the X's in the model. Other, more immediate operating factors in the refining section tend to dominate medium fibre length. However, the available chip characteristics were quite limited, with no information whatsoever about wood species, so it may simply be that chip quality is under-represented in the model.

It is important to emphasise that in the absence of a lesigned experiment, it is scientifically impossible to assign :ause-and-effect relationships to the PLS results. It may .imply be that certain X's trend with the Y's because both are eing affected by a third, hidden factor.

CONCLUSIONS

Although statistically significant PCA models were btained from the mill data, it is seems that the available chip lata do not tell the whole story. As a result, chip quality is robably under-represented with respect to refiner operating arameters.

Even though the low production points were removed, ulp throughput dominated the PCA results. This occurs even vithin a relatively narrow range of normal production rates. 'he reason is the large number of process variables that are lirectly or indirectly related to throughput.

Other than throughput, the inherent components that vere obtained for the system appear to relate to:

- Summer vs. winter, bleach consumption and pulp brightness;
- Fines fraction, fibre length, and specific energy;
- Refiner plate gap.

Using all the available data appears to have some dvantages in terms of the predictive power of the model. Iowever, groups of variables which are highly correlated tend o dominate the model, such that it may be necessary to give hem a lesser weighting in the future.

OMMAIRE

Des valeurs de procédé en amont et en aval des affineurs primaires et secondaires d'une usine de PTM ont té obtenues pour une période de 34 mois consécutives. Deux pes d'analyse multivariée ont été effectués sur des moyennes urnalières, soit l'analyse des composantes principales « PCA ») et la projection aux surfaces latentes (« PLS »), en tilisant différentes combinaisons de variables. Bien que des odèles statistiquement importants ont été obtenus à partir es données de l'usine, il paraît que les données sur les opeaux ne donnent pas un portrait complet. Aussi, le taux de roduction de pâte a dominé les résultats, même à l'intérieur 'une gamme assez restreinte de taux de production normaux. éanmoins, il a été possible de faire un premier essai aisonnable à une interprétation physique des composantes es modèles.

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APPENDIX VI:

Conference Paper – ESCAPE-13 2003

Processing of Thermo-Mechanical Pulping Data to Enhance PCA and PLS

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The purpose of this paper is examine what differences, if any, are obtained in multivariate analysis results using different time scales and averaging methods on compressed historical data. The data describe the operational performance of the refiner section of a modern thermo-mechanical pulp mill, a straightforward case whose feed and intermediate products have understandable physical and mechanical properties. Overall, it was found that medians give slightly better results than averages, and that goodness of fit of the model is heavily influenced by the sampling frequency of key process parameters.

1.0 Introduction

Seasonal variations, changes in incoming chip quality and other external factors that can affect pulp quality are often beyond the control of the thermo-mechanical pulp (TMP) mill operator. Many internal factors are controllable, however, and could possibly be used to counteract these external forces. The ultimate goal is to model in real time parameters that cannot be measured continuously, in order to apply inferential control ("soft sensor") as reported in Strand et al. (2001) and elsewhere (Kooi, 1994; Kresta et al., 1994). Before proposing any such control strategy, however, it is necessary to understand the correlations and trends which are inherent to the refining operation at the heart of the pulp mill, using historical data.

The Canadian TMP newsprint mill under investigation has had a high-speed PI data historian in place for 34 months, into which virtually all process and operating data for the entire mill are fed. The mill has over 6 000 data tags, some of which are updated every 10 seconds, potentially representing millions of numbers per day.

This data explosion has created a daunting mass of information, one for which the automated pattern-recognition techniques of multivariate analysis (MVA) are perfectly suited. The underlying principle of MVA is that useful patterns and relationships not intuitively obvious lie hidden inside enormous, unwieldy databases. Mill personnel have tried to establish relationships between the process variables by considering only a few at a time, an impossible task, hence their interest in co-operating with École Polytechnique on a new approach.

Final paper quality is of paramount importance to the mill, and can be influenced by many factors (Wood, 2001). Principle Component Analysis (PCA) of pulp quality and newsprint quality variables at the mill has shown that two pulp parameters, Medium Fibre Fraction and R48 Fibre Length Fraction, are strongly correlated with important paper characteristics such as permeability, stretch, burst strength and tear strength (Harrison et al., 2003). These two related parameters were therefore selected for the present study.

Previous papers on TMP operation that were reviewed used a variety of time scales, ranging from monthly averages to instantaneous readings (Lupien et al., 2001; Saltin et al., 1995; Shaw, 2001; Strand et al., 2001). The main purpose of this paper is to examine what differences, if any, are obtained in MVA results using different time-scales and averaging methods.

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2.0 Methodology

One of the mill's four pulp production lines was selected for study. Using the mill process and instrumentation diagrams, key data tags were identified on and around the primary and secondary refiners, including:

- Chip quality data (grab samples at the TMP feed conveyor, analysed in a laboratory): chip size distribution, bulk density, humidity.
- Refiner operating data, such as: throughput; specific energy imparted to the chips; energy split between the primary and secondary refiner; vertical and conical plate distances; dilution rates; levels, pressures and temperatures in various units immediately connected to the refiners; steam generation rate; voltage at chip screw conveyors; specific hydrosulphite consumption.
- Equipment data, such as: operational hours elapsed since refiner plates were last replaced or changed direction; number of refiners sending steam to heat recovery at any given moment; number of "feedguard" events, indicating refiner blockages; refiner body temperature.
- Pulp quality data (automated, on-line analysis of grab samples using Pulp Expert system): fibre length distribution; freeness; consistency; brightness.

Daily averages were extracted for the full 34 months, viz., November 23rd, 1999, to October 1st, 2002. To investigate shorter time scales, mill personnel helped to identify a recent typical operating week in which the chips were all from a single supplier, and no unusual production problems were encountered at the TMP mill: September 16th-22nd, 2002.

The first step for each run was to perform PCA on the entire dataset, to identify outliers and obtain an overall portrait. Periods of unusually low production (< 100 t/d) were excluded beforehand, as previous experience had shown these to produce major outliers systematically. Partial Least Squares (PLS) analysis was then performed using Medium Fibre Fraction (MFF) and R48 Fibre Length Fraction (R48) as the two Y's, and all other upstream data as the X's. Where applicable, a lag was introduced between the X's and Y's to account for the 45-minute residence time in the latency chest.

Of the many MVA outputs that can be generated using the Simca-P software, three dissimilar ones were selected for comparison: Variable Importance Plot to rank the X's in terms of importance to modelling the Y's; R^2 and Q^2 values for each of the two Y's; and Observed vs. Predicted to examine how well the PLS model can predict new Y's based on the X's.

3.0 Research Results

3.1 Establishing Time scales

Process data from the mill are stored in compressed form, i.e., only those values deviating more than ±1% from the previous stored value are kept. Compressed data can be extracted as:

- the actual stored data points, which will include significant time gaps, or
- interpolated, in which all time gaps are filled.

There are various other possibilities, such as for instance selecting the previous stored value.

The shortest time increment used at the mill in question is 10 seconds, which may be considered the lower limit. The system has been on line for 34 months, so one year could be considered the upper limit. It is possible to select virtually any time scale in between for analysing data for diagnostic purposes. In the refining section of the mill, there are several frequencies which guided the choices:

- Instantaneous pulp quality readings for Line 1 are taken every two hours, on average.
- Chip grab samples are taken from the TMP incoming conveyor every eight hours.
- The mill operates on three daily shifts of eight hours.

There are also computer limitations; for instance, it is not feasible to extract 10-second interpolated data for hundreds of tags over 34 months.

Figure 1 below illustrates the spectrum of available time scales in this case.

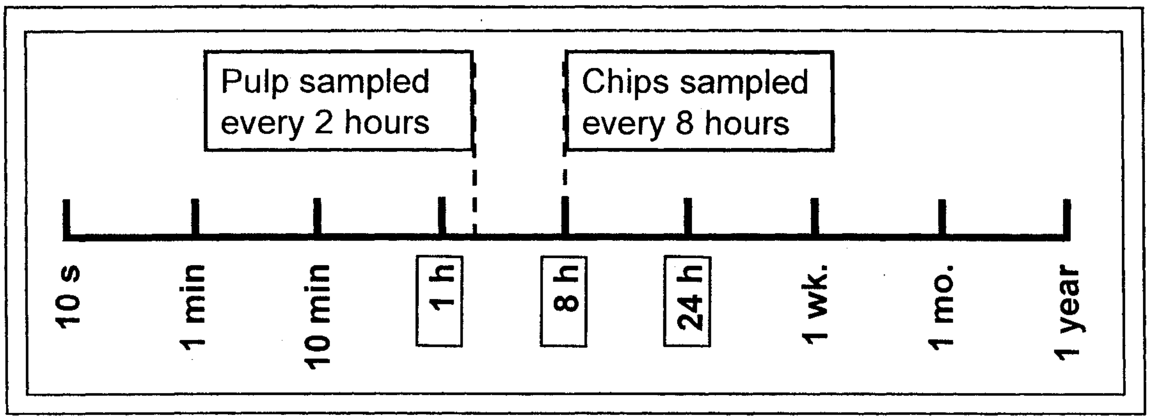

Figure 1: Range of possible time scales for system under study.

Three time scales were selected:

- 24 hours, encompassing three workshifts and three chip samples;
- 8 hours, corresponding to one workshift and one chip sample; and
- 1 hour, which is intentionally less than both the chip sampling frequency and the pulp sampling frequency.

One must also establish the averaging method. In the PI-Datalink software, the "average" function is a time-weighted mean, corresponding to interpolated data, whereas the "mean" function only uses the actual data points, thereby giving greater weight to periods where there are significant changes in the process. Both these options were used in the 8-hour case, along with the median value.

3.2 Overview of Entire Dataset

It has been shown that pulp refining data can be distilled into a small number of latent variables or components using MVA (Broderick et al., 1995). In a previous study at the same mill (Harrison et al., 2003) daily averages over several years yielded four major PCA components, the most important of which was Line 1 throughput. The next two components appeared to be strongly related to seasonal variations in chip quality, and the fourth to refiner plate gap.

An important outcome is that even when the low production points are removed, throughput continues to dominate other variables when using multi-year data. This occurs even within a relatively narrow range of normal production rates. This is probably due to the large number of variables that change when the throughput changes, such as dilution flows, screw feeder motor voltages and so forth. In contrast, when the period is reduced to just one week, the production rate becomes less influential so long as the major valleys are removed.

In performing PLS analysis with MFM and R48 for Y's, it was found that the PCA score plots for the remaining hundred-plus X variables strongly resembled those for the entire dataset, which will greatly facilitate the eventual physical interpretation.

3.3 PLS with Different Time Scales and Averaging Techniques

No major problems were encountered in performing PLS at the various time scales. Linear interpolation was used for the chip and pulp quality data at the 1-hour time scale. The fit of all the models was reasonably good, with R^2 values between 0.66 and 0.92, and Q^2 values of 0.56 to 0.72. Of course, all the runs were performed on only one week of data, meaning that the models' ability to predict other weeks is probably much lower.

3.4 Shorter Time Scales

With modern computers, it is possible to extract one week's worth of data for hundreds of tags at 10-second increments. This requires linear (or other) interpolation between compressed data points. It would also require some form of interpolation for intermittent measurements, such as the 2-hour pulp quality grab samples, an extremely gross approximation. The use of the previous recorded value is also of no use in this case, since Simca looks for variables which tend to move at the same time, and is "fooled" into thinking that a major process shift is occurring every two hours or so.

The same argument applies, to a lesser extent, to shorter averaging time scales such as 1 minute or 10 minutes. To perform a PLS at such a temporal resolution, a much more frequent pulp sampling campaign would be required. Residence times in the different unit operations would also have to be known to an equivalent precision, to ensure that all time lags are accounted for during the data pre-processing.

In conclusion, shorter time scales can be used to model individual sections of the refining process, for which frequent data is available, but in this case they were not appropriate for modelling the overall process from chips to pulp.

4.0 Comparison of Different Data Processing Approaches

4.1 Relative Importance of X's to PLS Model

Variable importance plots for 1-hour, 8-hour and 24-hour averages showed the same handful of X's dominating, regardless of time scale, though sometimes the relative order of the X's would switch. Among the rest of the X's, the main difference was that chip size distribution had virtually no impact on the 1-hour averages, supporting the notion that even shorter time scales would be of no use in this case. Overall, the chip data resolved best at the 24-hour time scale, probably because the inherent variability of the grab samples was partly compensated by the levelling effect of the averaging over three readings.

4.2 Goodness of Fit of PLS Model

PLS Q^2 values for the Medium Fibre Fraction variable were generated for each of the runs (Figure 2). While the 8-hour average was not much better than the 1-hour average, the 8-hour median did show a significant improvement. It appears that the median is a better representation of the 8-hour workshift than the average, which may be unduly influenced by minor, short-term perturbations. Note that the median MFM value was also used in this case. The "mean" averaging technique gives a poorer result, and is probably not appropriate for this type of application.

One interesting outcome is that the 24-hour average fared the poorest. This means that this model predicts individual days less well than 8-hour shifts. This may simply be a case of too few data points. When the entire month of September was included, the Q^2 improved, but the important X's changed radically, meaning that it was no longer the same model.

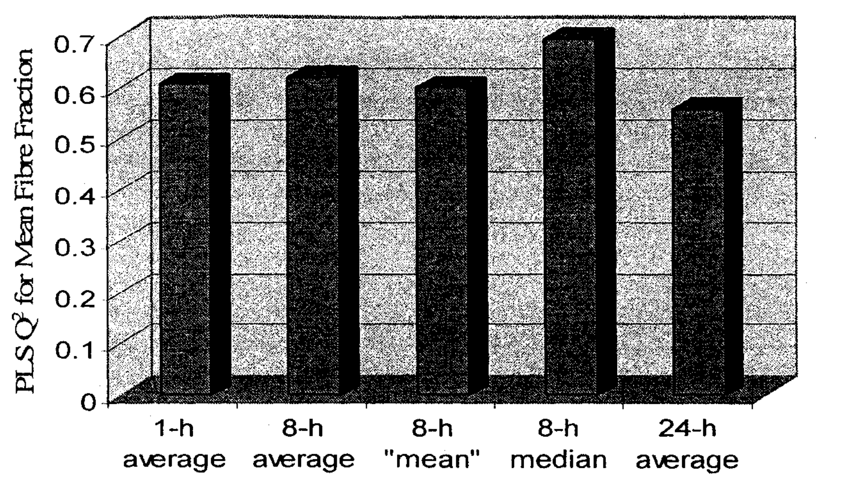

Figure 2: PLS Q^2 values for Medium Fibre Fraction.

4.3 Observed vs. Predicted

Another method of comparing the outputs is to plot the actual observations for each time increment against the value the model would have predicted if given the corresponding X data as an input. The degree of scatter in Figure 3 shows that the 8-hour model comes closest to fitting the ideal 45° line. The most likely explanation is that the 1-hour time increment is lower than that of the pulp quality readings, such that the Y values for some of the hours are really averages of purely interpolated data only. The 24-hour average shows significant and non-normally distributed scatter, probably due to the low number of data points.

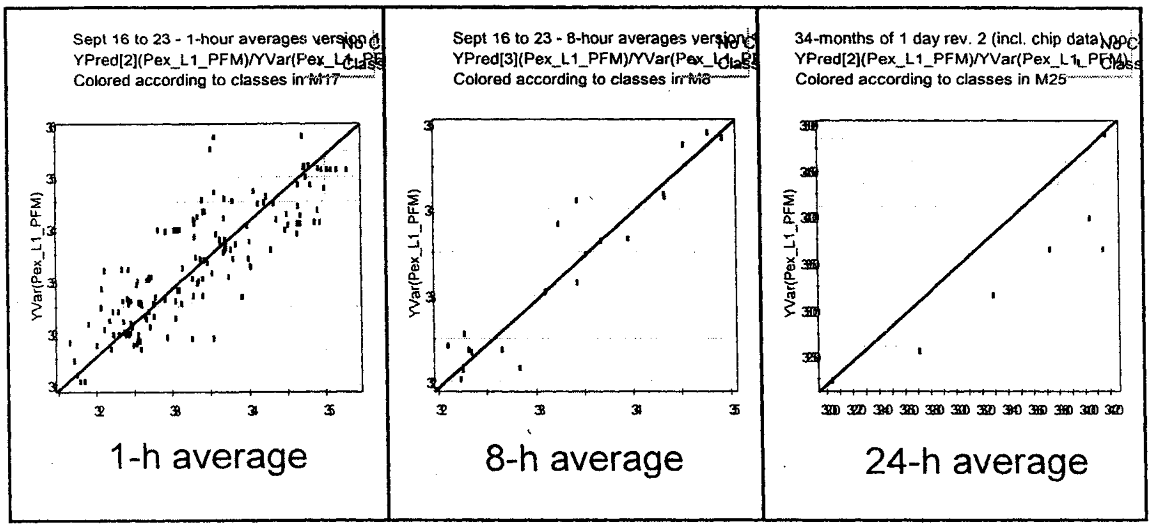

Figure 3: Real observation (ordinate) vs. PLS prediction (abscissa) for different time scales.

5.0 Conclusions

Overall, it was found that low production points tend to dominate other variables, and so must be treated separately, and that medians give slightly better results than averages. Specific recommendations are to:

- Remove low production days using a percentile or threshold.
- Use medians instead of averages, if possible.
- The optimal time scale depends on the intended application. Generally, the same X variables are prominent regardless of the time scale used, but the goodness of fit of the model is heavily influenced by the sampling frequency of key process parameters.

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Keywords: Multivariate analysis; pulp quality; refiner operation.

Proposed thematic group for ESCAPE-13 conference, Lappeenranta, Finland: Modeling and simulation of unit operations in pulp and paper industry

APPENDIX VII:

Conference Paper – PAPTAC 2005

REPRESENTING TMP PROCESS FUNDAMENTALS BY CREATING NON-LINEAR VARIABLES IN MULTIVARIATE ANALYSIS

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ABSTRACT

Multivariate Analysis (MVA), a statistical technique for :eating large datasets, is increasingly being used to :oubleshoot TMP mills or to create 'soft sensors' for dvanced process control. Despite the vast quantities of rocess operating data now readily available via data istorians, many fundamental variables go unmeasured, or are neasured only infrequently relative to the residence time in ne refiner. MVA models are linear, so any highly non-linear arameters such as cross products must be accounted for head of time. In this study, a variety of new variables were ntroduced into a PLS (Projection to Latent Surfaces) model of ewsprint tear strength at an Eastern Canadian TMP mill. 'hese new variables were constructed from existing ones, ased on the fundamentals of the TMP process. Among the ew variables were the standard deviation, variance, and ogarithm of key TMP parameters, as well as non-linear ombinations of several operating variables to reflect refining ntensity in a conical refiner. Creating indirect indicators of efining intensity in the MVA models gave promising results, espite the lack of information on incoming chip haracteristics.

NTRODUCTION

Multivariate analysis (MVA) techniques were applied to istorical data from a TMP newsprint mill in Eastern Canada, › better understand the correlations and trends that are nherent to the refining operation. These statistical techniques erve to reduce the dimensionality of a system by creating a andful of "latent variables" constructed from the original ariables [1, 2, 3, 4].

One of the overall goals of this research project is to orrelate final newsprint characteristics such as tear strength to perations in the TMP section, to the extent possible when sing real plant data. It is well established that average ength-weighted fibre length is a critical factor with respect to ear strength [3], and so this parameter was retained as a key ulp quality indicator, along with freeness which is the main arameter used by the operators at the mill under study. The nitial focus of this work has been on the primary and econdary TMP refiners and the latency chest pulp, but ventually this work will extend to the paper section as well.

The specific goal of this article was to determine if it is ossible to more accurately represent TMP fundamentals by reating non-linear terms from the measured variables.

METHODOLOGY

The overall methodology for this research project was described in an earlier paper [5]. In the present case, however, we used some shorter timescales, namely 1-hour increments over a period of 2 to 4 days. Also, several new non-linear variables were created from the existing ones, as described below.

SEASONAL CHIP AND PULP QUALITY

The mill has minimal chip inventory, and a variety of outside chip suppliers. Usually the exact source and softwood species are unknown. Size, density, and humidity are measured in a lab using grab samples collected every 8 hours at the chip silo feed conveyor, which feeds all four TMP refiner lines.

Multivariate analysis of these chip parameters over three years, using daily averages, yielded very poor statistical models. It was found that there was little or no correlation among the measured chip characteristics other than a strong summer-winter trend that was already well known to mill personnel, with smaller, denser, wetter chips prevailing in the winter. Furthermore, no significant correlation was found between the measured chip characteristics and the mainline pulp quality, other than according to seasonal variations. These findings would indicate that the chip quality data are too sparse and limited to be useful for this kind of statistical analysis, and confirm the need for better measurement tools for incoming chips such as optical scanners [6].

In order to better characterise the seasonal trend, latency chest pulp quality parameters were compared to ambient temperature, measured as the average monthly temperature from a nearby Environment Canada meteorological station. A time lag of 60 to 80 days was found, depending on the pulp parameter in question. For example, average fibre length, which varied from 1.2 mm to 1.5 mm throughout the year, was compared to ambient temperature in a cross-correlation plot in Figure 1. This plot shows how the coefficient of correlation changes when a lag is introduced between the two variables; the highest coefficient, and hence greatest correlation, occurs when temperature is shifted by about 80 days relative to the fibre length (the two shorter horizontal lines define the zone of statistically insignificant correlation).

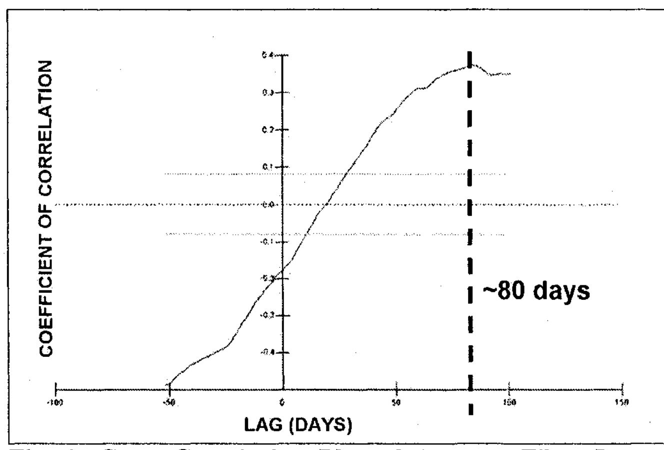


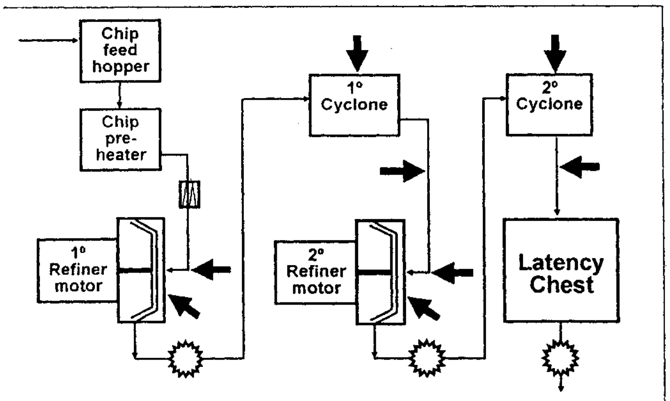
Fig. 1. Cross-Correlation Plot of Average Fibre Length versus Season

This trend confirmed an observation by mill personnel that the most typical "winter" operating conditions occur in

March, and the most typical "summer" conditions are in August, a lag of about 60 days. This is thought to be due to the time from tree felling to chip use. Therefore, the time periods selected for the purpose of this study were the months of March and August over two consecutive years, 2003 and 2004. In each case, the longest possible uninterrupted periods of full production were used.

PLS MODEL

The section of the plant under investigation is illustrated in Figure 2. The mill is equipped with Sunds Defibrator CD-70 refiners, with independent control for vertical and horizontal plate gaps, and multiple dilution points as indicated by the bold arrows. There is no advanced process control on these refiners; all key operating decisions are made by the operators.



'ig. 2. TMP Section. Dilution points are indicated by bold ırrows, and pulp sampling locations are indicated by stars.

PLS (Projection to Latent Surfaces) models serve to naximize the covariance between a set of X variables, in this ase operating data from the primary and secondary refiners, nd a set of Y variables, namely the latency chest pulp quality. 'he variables included in the model are listed in Table I, along /ith the non-linear operations that were applied to each.

TABLE I: VARIABLES USED IN PLS MODEL

'ARIABLE OR GROUP OF 'ARIABLES	NON-LINEAR OPERATION
-Variables	
' & 2° motor loads	standard deviation
roduction rate (proportional to feed :rew rotational speed)	division (specific energy)
' & 2° vertical plate gap	none
' & 2° horizontal plate gap	none
' & 2° dilution flows (multiple)	none
& 2° steam pressure drop across finer	cross product
& 2° hydraulic pressure delta	cross product
& 2° blowline consistency	cross product
Variables	
ınadian Standard Freeness	logarithm
/erage length-weighted fibre length	none

The decision as to whether a given variable is included in the X set or in the Y set is left up to the user; in this case, blowline consistency was placed among the X's, since it is used here as an indicator of low refining intensity. Other variables, such as plate age, were also obtained from the data historian, along with the set points inputted by the operators. While not used directly in the model, these served to characterize the operating periods under study.

A major challenge in this study was the constant starting and stopping of the TMP lines, due to over-capacity relative to the papermaking section. To overcome this problem, the PLS model was limited to periods of full production.

Is it well established that data compression can impact mean and standard deviation calculations [7]. However, since MVA is focussed entirely on trends, and not on absolute values, this may not have much impact. In an upcoming series of trial runs, the data compression will be removed to gauge its real impact on this kind of MVA application.

CREATION OF NON-LINEAR TERMS

The components that make up MVA models are simply linear combinations of the original variables. To accommodate non-linearity in such models, new variables can be created based on one or more of the original ones. The most obvious example related to TMP is specific energy, which represents the division of one original variable by another, namely motor load by throughput. Using the two original variables alone, without specific energy, yields a poorer statistical model since in combination they correspond better to the process.

Some of the specific energy values encountered in the data historian were nonsensically high, sometimes by two orders of magnitude. This appears to have been caused by automated calculations over very short time periods using a near-zero denominator value for throughput. Thus, for the purposes of this project, all specific energies were calculated directly from the one-hour averages for motor load and throughput. This technique not only removes extreme values, but also seems to smooth the specific energy curve compared to data historian values.

Multivariate statistics have been used to understand and ultimately reduce process variation in a variety of sectors [8]. With variability being such a key concern in TMP operations, past authors have used the variance of certain key parameters like motor load as a new variable in MVA modeling [1, 3]. The reasoning is that the degree to which the motor load fluctuates is an indicator of process stability. The standard deviation of this variable (the square root of the variance) is readily available from the data historian, and so was included as a non-linear variable.

Freeness is often linearised by taking its logarithm, as was done in a recent MVA paper [9], to allow for easier interpretation. To determine whether linearization of freeness data is appropriate also for the TMP operation being studied, both the logarithm and the original values were used. It should be noted that it does not matter which type of logarithm is used, since all variables are normalised before use in the MVA model.

MODELLING OF REFINING INTENSITY

Refining intensity is defined as the specific energy delivered per refiner bar impact. Excessive refining intensity can damage fibres, even when specific energy and freeness appear normal, leading to reduced fibre length and tear strength [10]. In other words, when refining intensity is high, the freeness is achieved through fibre cutting instead of fibre development, resulting in the type of gain reversion described by Roche *et al* [11].

In a conical refiner it is difficult to model refining intensity directly, as no equations analogous to the Miles and May model have been published for this type of refiner. The goal was therefore to model refining intensity indirectly, if possible, using existing measured variables. As is the case with most MVA studies of existing operations, results are dependent on the natural variability pre-existing in the dataset.

For a given plate configuration and disc rotation speed, refining intensity is largely a function of refining consistency [11]. This is an inverse relationship, since greater consistency means a longer residence time between the refiner plates and hence more bar impacts for a given specific energy. As a first approximation, blowline consistency was therefore used as one of the indicators. The mill has no on-line instrument to measure blowline consistency, but there is a real-time, on-line calculation based on a mass/energy balance, verified by off-line grab-sample measurements taken every 3-4 hours. While these two sets of values do not match perfectly, they were found to have a correlation coefficient of about 0.5 with zero lag. The grab samples were far too infrequent to be useful, so the on-line algorithm value was used in the PLS model.

Another parameter used to indicate low refining intensity was the difference between casing pressure and steam inlet pressure at the refiner. Higher casing pressure indicates more backwards steam flow, retarding the outward pulp flow caused by the rotation of the disks and hence increasing residence time of fibres between the refiner plates. A third parameter, the difference in "B" and "A" hydraulic pressures, is often used as an indicator of refiner operating stability and was also included for comparison.

Two combinations of these three parameters were inserted in the PLS model, to see whether an empirical "low refining intensity" factor was pertinent in describing variability in the Y-parameters. The first, arbitrarily denoted LRIJ, is the product of all three, and the second, LRIK, is the cross-product of blowline consistency and steam pressure drop across the refiner. The cross-product was used since this will be highest when all the original variables are higher than usual, and lowest all are lower than usual. Clearly, the numerical values and units of these factors are meaningless, but the goal was to provide the statistical model with dummy variables that indicated the most favourable refining conditions.

Refining intensity in the secondary stage has been shown to have a significant impact on softwood pulp quality [12, 13], and it is generally desirable to have lower refining intensity in the second stage to avoid excessive fibre cutting. Because of the nature of multivariate statistics, which can tolerate both correlated and uncorrelated variables, it was possible to include both the primary and secondary refiner operating variables in a single model. Theoretically, any independent operation between them should appear as separate components.

PLS MODEL WITH NEW TERMS

The intial PLS model, using just the original variables, was compared to updated models using the non-linear terms for four different time periods, as presented in Table II. Note that the plates have a normal lifespan of about 2000 hours.

TABLE II: TIME PERIODS STUDIED

DATE	DURATION	PLATE AGE
March 7-10, 2003	80 h, full production	1° : 400 h 2° : 1900 h
August 7-11, 2003	100 h, full production	1° : 300 h 2° : 800 h
March 12-14, 2004	40 h, full production	1° : 100 h 2° : 1000 h
August 8-12, 2004	70 h, full production	1° : 1900 h 2° : 1600 h

Using the original variables, fairly good PLS models were found for freeness, with Q^2 values ranging from 26% to 72%. Q^2 is a goodness of fit analogous to R^2, but specific to predictive power (it is the percentage of overall measured variance that is attributable to the model's predicted values). The PLS models for average fibre length were much weaker with Q^2 ranging from 23% to 27%. Secondary refiner characteristics tended to dominate throughout. The models derived from summer data were generally better. For August 2004, no statistically significant PLS model was found for average fibre length, indicating that this variable did not exhibit significant correlation with the others; this was possibly due to unmeasured and significant variations in chip properties.

In general, it was found that replacing the three original "low refining intensity" indicators with one or both non-linear terms marginally increased Q^2 for the model, for both freeness and average fibre length. Sometimes Q^2 remained essentially the same, indicating that the new terms captured the information contained in the original variables but did not improve the PLS model. Other approaches were also tried, such as dividing the original variables instead of multiplying them, or combining them with specific energy, but these were found to have little or no correlation with the rest of the dataset.

The PLS model for freeness for the August 2003 period showed only a slight increase in Q^2 when the three variables were replaced by LRIK (from 51% to 52%), but resulted in a reduction in model dimensionality: the model changed from having two components to having only one. This sort of transformation can be a benefit in itself, by rendering interpretation of the PLS model more straightforward. An equivalently powerful model with fewer components probably corresponds more closely to the basic elements of the system. When both non-linear terms were added, Q^2 rose to 54%, again with only one component.

For this last case, Table III lists the largest PLS "loadings", the weightings assigned to each original variable by the PLS model. The loading for the Y variable, freeness, is positive, as is the loading for dilution flowrate. This indicates that these two variables tend to increase and decrease in tandem, to the extent to which the model is significant. All the other X variables are negative, indicating that they tend to increase when freeness decreases, and vice versa. The largest loadings, in absolute value, are LRIJ and LRIK, indicating that these two new terms contributed significantly to the model.

TABLE III: PLS LOADINGS FOR SELECTED SECONDARY REFINER VARIABLES – AUGUST 2003 PERIOD

/ARIABLE	PLS LOADING
{-Variables	
:° motor load	-0.322287
:° specific energy	-0.325208
;td. deviation of 2° motor load	-0.26106
° dilution flowrate	0.224186
:reated term: LRIJ	-0.365698
:reated term: LRIK	-0.424421
'-Variables	
:anadian Standard Freeness	0.316793

Plate gap, though of major importance to the TMP rocess, did not figure consistently in the models. In some ases, only one of the four plate gaps was found to be orrelated with the pulp quality values, in other cases all four 'ere found to be correlated, sometimes positively, sometimes egatively. It is likely that taken over a period of only a few ıys, plate gap is more of an indication of operator decisions an of the conditions affecting the fibres.

The standard deviation and variance of the motor load nded to follow the trends in motor load itself, and so added tle to the PLS models. It may be necessary to test these ıriable over longer time periods, or to find a more suitable ay to represent the variability of the refining operation, such the coefficient of variation.

Using the logarithm of the freeness, instead of the iginal CSF value, made virtually no difference to the PLS odel. It is likely that the freeness did not vary over a large ough range.

SCUSSON OF RESULTS

PLS outputs must be studied carefully, to ensure that the ;ults correspond to the known properties of the system at nd. The PLS models from this study were consistent with pected results, such as for instance, lower specific energy ing associated with less fibre development (higher freeness) d less fibre cutting (longer fibre length).

However, for both the winter and summer examples, the re length was found to be higher when the "low refining ensity" variables were *lower*, i.e., when the refining ensity was presumed to be *higher*. This paradox is almost tainly due to unmeasured fluctuations in incoming chip perties affecting both the final pulp fibre length and the iners themselves. This highlights the caution that must be en when analyzing data taken under uncontrolled ıditions.

NCLUSIONS

Multivariate analysis (MVA) techniques were applied to orical data from a TMP newsprint mill in Eastern Canada, order to determine if it is possible to more accurately esent TMP fundamentals with a variety of new non-linear variables constructed from measured variables. The new variables were introduced into a PLS (Projection to Latent Surfaces) model of pulp quality. It was found that the incoming chip quality measurements were too sparse and limited to be useful in this kind of statistical exercise, confirming the need for better analysis of incoming chips.

Creating indirect indicators of refining intensity in the MVA models gave promising results. Blowline consistency derived from a mass/energy balance, steam pressure drop across the refiner, and hydraulic pressure delta were all found to be significantly correlated with freeness and average fibre length. Replacing these terms with their cross-products yielded only marginal improvements to the models. No significant differences were found between the summer and winter models.

The inclusion of standard deviation, variance, logarithm and other non-linear operators was found to have little impact on the MVA models, at least for the parameters and time periods that were studied. Clearly there is a need to better capture the variability of the TMP process for this kind of statistical modelling, and this avenue of research will continue to be pursued.

Some unexpected results were found, such as higher average fibre length corresponding to higher refining intensity. This is likely due to unmeasured fluctuations in incoming chip characteristics affecting both the pulp quality and the refiner operation, and highlights the extreme caution that must be taken when using raw process data.

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SOMMAIRE

Des modèles de type Projection aux surfaces latentes (« PLS ») ont été bâtis à partir de données d'opération d'une usine de papier journal dans l'est du Canada, dans le but éventuel de modéliser la force du papier. Pour mieux représenter les fondements du procédé PTM, notamment l'intensité de raffinage dans les raffineurs coniques, de nouvelles variables non-linéaires ont été créées à partir des variables mesurées aux raffineurs primaires et secondaires. Parmi les nouvelles variables on retrouve l'écart type, la variance et le logarithme, ainsi que le produit de plusieurs variables prises ensemble. Cette approche a servi à créer des modèles statistiquement importants, malgré le manque de données sur les copeaux fournis à l'usine.

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APPENDIX VIII:

International Peer-Reviewed Publication – 2006 – Tappi Journal

Linking pulp variations to TMP operation by better selection and treatment of process data

ROBERT P. HARRISON AND PAUL R. STUART

ABSTRACT: Multivariate analysis (MVA) is widely used for troubleshooting, process monitoring, and advanced control. It has become easily accessible through desktop software packages. However, this least-squares statistical technique remains highly susceptible to the adage "garbage-in/garbage-out," notably with regard to process disturbances and other outliers. Using a thermomechanical pulp newsprint mill in Eastern Canada as a case study, we compared various ways of selecting and pre-treating raw process data to maximize the realism and usefulness of the black-box pulp quality models. We eliminated start-up and shutdown data to model steady-state conditions. A major conclusion of this work was that the partial least squares models were significantly improved by pre-treating the data, with respect to both statistical significance and physical interpretability. We therefore recommend an overall approach for applying MVA to industrial operating data. This involves a systematic method for removing dubious periods of operation, such as low production and aberrant process behavior, and filtering of all dependent and independent variables. Because no single model was able to cover all process scenarios, it seems that some kind of adaptive controller would be required to automate the TMP refining process.

Application: This study presents a straightforward method for selecting and pretreating TMP operating data, to improve statistical tracking of pulp quality variations.

Multivariate analysis (MVA) is increasingly being used for improving operations, whether through troubleshooting, process monitoring, or advanced process control. This statistical tool is widely available to plant personnel via user-friendly desktop computer packages, but it is highly susceptible to "garbage-in/garbage-out." This paper uses historical data from a real mill to explore ways to counter this challenge.

MVA reduces the number of variables within a dataset, to make it more manageable and understandable. The original variables are boiled down to a smaller number of new variables, or 'principal components,' that typically capture much of the variance of the initial dataset [1]. Each principal component is simply a linear combination of the original variables. Often, the principal components will correspond to hidden or latent variables, inherent to the system, that are not measured directly but have a physical interpretation. Modern computing power has made it possible to apply MVA to millions of data points, and it has been used in a variety of industrial sectors [2], including pulp and paper [3-6].

MVA is a statistical technique, entirely data-driven. It functions like a black box, finding relationships between input and output data only, with no physical modeling of any kind. As a least-squares method it inevitably overemphasizes extreme values such as large process fluctuations, at the expense of normal operating conditions. When applying MVA to raw data from an industrial facility such as a pulp and paper mill, it is therefore critical to select and pretreat the data adequately.

CASE STUDY: TMP NEWSPRINT MILL IN EASTERN CANADA

The case study for this project is a thermomechanical pulp (TMP) newsprint mill in eastern Canada. The mill experiences short- and long-term variations in final paper quality. Over a typical month, hourly averages for tear strength, burst, and tensile stiffness index (TSI) may vary ±10%. Within a calendar year, daily averages for these same parameters may vary ±12%-14%. The goal of the study was to use MVA to understand the correlations and trends that are inherent to the mill operation to determine which upstream parameters are most likely linked to pulp quality variations.

High-quality pulp requires good quality fibers that are well separated. Proper refiner operation is critical to this aim, with maximum separation, but minimum cutting of fibers. Changes in incoming chip quality are beyond the control of the TMP mill operator, and are difficult to measure [7]. To a certain degree, these external factors could theoretically be counteracted using controllable internal operating parameters such as chip feed rate, specific energy, dilution water flow, and plate gaps.

Typically, TMP operators use freeness as the main indicator of pulp quality, adjusting the set points for three variables: transfer screw speed, plate position (or hydraulic pressure), and dilution water flow rate [8]. The specific energy required to achieve a given freeness is usually related to the amount of long fiber in the pulp [9]. Modern control systems [3, 10] therefore use freeness and fiber length as indicators, generating a window within which the refiners should operate.

At the case study mill, key pulp quality parameters, including freeness, average fiber length, and fines content, are measured using an automated on-line Metso PulpExpert EXP sampler/analyzer. The mill operates on 100% wood chips, using a combination of black spruce and balsam fir, but no substantial data were available on the incoming wood chip quality or exact species mix. (Several on-line woodchip monitors are under development in Canada, though none is yet commercially available.)

The mill is equipped with Sunds Defibrator RGP-70-CD conical refiners, with independent control of the gap between the plates in both the flat and conical sections. There is no advanced process control on these refiners; key operating decisions are made by the operators. The main steps are:

1. Steam pre-heating of chips at 180 kPa for 3 min
2. Primary refining at 350 kPa and 40%-50% consistency
3. Secondary refining at 350 kPa and 40%-50% consistency

The latency chest has an approximate residence time of 45 min. The upstream equipment has a residence time of only a few minutes, so in this regard the latency chest dominates this section of the mill. The refiner plates have a normal lifespan of about 2000 hours.

Pulp refining is a highly complex process using a biological feed material, so fundamental models to date have been semi-empirical [11]. However, no models have been published specifically for conical refiners, hence the necessity of the black-box approach used in this study. The MVA models presented here are based on previous work that focused on identifying key variables, and their combinations, to best model the fundamentals of this system [12].

RELATING PULP VARIATIONS TO TMP OPERATION

A variant of MVA called *partial least squares* (PLS) was used to model latency chest pulp quality. As shown in Table I, the pulp quality parameters which serve as the Y variables were freeness, average fiber length, and percent fines. We selected a time increment of 1 hour, corresponding roughly to the overall residence time of the system (around 50 min). The three dependent variables are measured every 60-90 min on average, and so again a 1-hour period is appropriate.

A major challenge in this study was the regular starting and stopping of the TMP lines, due to built-in overcapacity relative to the papermaking section. Direct use of the raw data would yield meaningless MVA results, because the algorithm would attribute most of the correlation to the start-stop phenomenon, and not to actual changes in the process during normal operation.

As is the case with most MVA studies of existing operations, results are dependent on the natural variability pre-existing in the dataset. Designed experiments can be used to counter this problem [13]. However, this study was limited to historical operating data which, though imperfect, are an important (and inexpensive) source of insight available to process engineers.

Variable	Unit
X variables	
1° and 2° motor loads	MW
Production rate	
(proportional to feed screw rotational speed)	tons/day
1° and 2° specific refining energy	kWh/ton
1° and 2° flat plate gap	mm
1° and 2° conical plate gap	mm
1° and 2° dilution flows (multiple)	L/min
1° and 2° steam pressure drop across refiner (iP)	kPa
1° and 2° blowline consistency (calculated)	% solids
1° and 2° plate age	h
Y variables	
Canadian Standard Freeness	mL
Average fiber length (length-weighted)	mm
Fines content, defined as small enough to pass through 200-mesh screen (76 m)	%(mass)

Table I. Variables used to generate partial least squares (PLS) model of single thermomechanical pulp line at case study mill.

Criterion	Parameter Used1	Type Of Output
Goodness of Fit	Q^2 for overall model Predicted vs. observed for each Y	Quantitative Scatter plot
Complexity of Model	Number of components required for a given Q^2	Quantitative
Realism of Model	Relative prominence of X variables Interpretability of components with regard to process fundamentals	Ranking Qualitative

[1]Q^2 is a measure of goodness of fit analogous to R^2, but it is specific to predictive power; it is the percentage of overall measured variance that is attributable to the model's predicted values. It is derived by separating the dataset into several segments, some used to create the model, others for testing it. Unlike R^2, which increases when a model is made more complex with additional principal components, Q^2 tends to plateau and then diminish when there is over-fitting.

Table II. Criteria used for comparing MVA models.

The various MVA models generated in this study were evaluated using two different, but parallel, approaches: *mathematical*, primarily based on goodness of fit; and *physical*, based on the interpretability of the components that were found. Table II lists the criteria used in this project.

We subjected the raw data to the step-by-step approach outlined in Fig. 1. We evaluated each of the preprocessing steps to compare and contrast the results obtained. For the most part, data pretreatment was done in Microsoft Excel before downloading the data into the MVA software: SIMCA-P (version 10) from Umetrics AB.

Minimum production, as opposed to mean production, refers to the smallest value recorded on a second-by-second basis within that 1-hour period. A threshold of 200 tons/day was selected because the TMP operators never intentionally operate the refiners below this rate.

We used *principal component analysis* (PCA)—the other main variant of MVA—to identify potential outliers. It differs from PLS in that it treats all variables the same, rather than dividing them into Xs and Ys. In fact, PLS is a combination of one PCA model for the Xs and another for the Ys, each one tweaked to match each other (hence the name "*partial* least squares").

PCA "score plots" show how each observation fits within the model space relative to all the others. The "distance-to-model plots" show how far each data point had to be projected to be included in the model. To eliminate subjectivity in interpreting these plots, only points falling outside Hotelling's T^2 (95-percentile) were considered outliers. The Simca-P software shows this threshold as an ellipse on the score plot, and as a horizontal line on the distance-to-model plot [14]. To identify which variables caused the outlier in the first place, we used the MVA "contribution plots." This ability is one of the main advantages of MVA over other black-box methods.

Exponentially weighted moving average (EWMA) is the most widely used form of filtering in the chemical process industries. Trimming and "winsorizing" automated features of the Simca P software [14] serve to remove extreme values. (Winsorizing is statistical jargon for replacing extreme values with the value at the cut-off point.) Since these features are routinely employed by MVA users, they were included in this study for the sake of comparison.

The periods under study were based on previous work in which the significance of summer and winter periods were examined [12]. Identical periods (March and August) were used within two separate years (2003 and 2004). The mill used normal refining plates during these periods.

REMOVAL OF LOW-PRODUCTION PERIODS

The main cause of production disruptions at the refiners is built-in overcapacity relative to the paper machines. When less pulp is needed, one of the four refining lines is temporarily shut down, such that the mill is operating with only three refiner lines about 70% of the time. All four lines are subjected to these shutdowns. Automatic shutdowns, called "feedguard" events, are triggered by excessive motor load and represent another cause of production disruption. Also, the refiners are stopped every 200 hours to change the direction of disk rotation, to prevent uneven

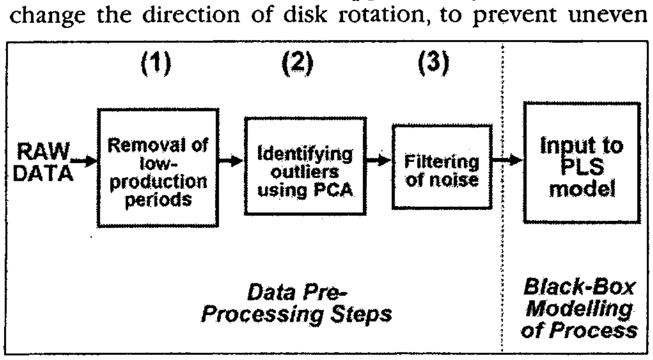

Figure 1. Overall data pretreatment strategy applied to TMP historical data.

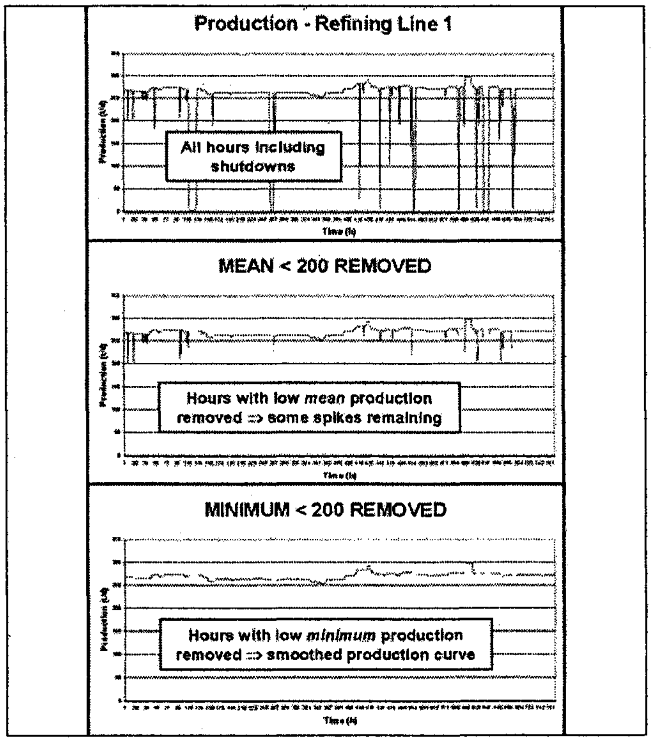

Figure 2. Hourly production rates for refining line 1 (expressed as metric tons per day) for the month of August 2003.

wear of the refiner plates.

August 2003 was selected as the base case. Previous work at the mill had shown stronger MVA models for summer data, possibly due to poorer chip quality in winter. The two options for dealing with low production periods were compared. On the basis of the mean throughput, 58 hours were disqualified out of 768 for August 2003. Only removing periods where the mean production was below the threshold proved inadequate, however (Fig. 2). The mean in this case disguised short periods of low production. Using the more stringent minimum test, a further 32 hours were removed, which resulted in a much clearer picture of the overall periods suitable for further study.

To complete the comparison, PLS models were generated using different datasets (Table III). The Q^2 shown is a combined metric for all three dependent (Y) variables, namely latency chest freeness, fiber length, and fines content. In other words, these models were built for a group of dependent variables. The results obtained would be different if each dependent variable had been modeled separately.

Thus, the PLS results for August 2003 confirmed that the best option was to remove *a priori* the periods with minimum production below the threshold, and then take out the PCA outliers. However, the differences between some of the Q^2 values are slight. In the case of "mean < 200 removed" there was no appreciable difference when the outliers were removed. It was therefore necessary to investigate further by examining the actual nature of the data points that were removed in each case.

IDENTIFYING MAJOR OUTLIERS

For each of the four months under study, we created a PCA model using all variables and data points, including low-production periods, to test the effectiveness of MVA for detecting known outliers. The data points identified using Hotelling's T^2 ellipse (95-percentile) often corresponded to the periods of low production, but not always, and some low production periods were not detected at all.

Some of the outliers detected using the distance-to-model plot occurred during normal production periods, several hours after the last shutdown. Clearly, other variables were breaking with the model structure. Studying the contribution plots revealed that, for these points, plate gap and specific energy in the secondary refiner were higher than normal in some cases, and lower than normal in others. Several points showed higher or lower specific energy in the primary refiner. These results are difficult to interpret, because the residual low-production periods could be adversely affecting the model's overall validity.

Next, a PCA model was created that excluded periods of low *mean* production. The score plots revealed far fewer outliers, corresponding to periods where the minimum production was below the threshold. The distance-to-model plots also showed fewer outliers.

Finally, we created a PCA model excluding periods of low *minimum* production. This resulted in the model with the fewest outliers. For August 2003, fewer than 10 outliers were found on the score plot, with a further 32 found on the distance-to-model plot. This explains why there was no appreciable difference in when the outliers were removed.

Using the MVA contribution plots for these points, we could determine which variables had caused them to break with the overall correlational structure. The few dozen distance-to-model outliers were mainly due to changes in pulp parameters that were uncorrelated with the other variables, or to fluctuations in steam pressure drop across the refiner, possibly indicating temporary obstructions to counter-current steam flow between the refiner plates. Overall, this small number of outliers appeared to represent unusual operating conditions. Even though they had little effect on the Q^2, they were therefore removed before continuing to the next step of data pre-treatment.

Dataset	Overall Q^2	# of Comp.[2]	Comments
All hours	22%	5	Dominated by start-up and shut down
- minus outliers[1]	41%	5	Dominated by start-up and shutdown
Mean < 200 removed	39%	5	Start-up and shutdown still strongly evident
- minus outliers	39%	4	Start-up and shutdown still strongly evident
Min. < 200 removed	40%	4	Minimal evidence of start-up and shut down
- minus outliers	41%	4	Option retained

1Rows marked "- minus outliers" indicate that both types of PCA outliers were removed.
2The column identified as "# of Comp." refers to the number of significant components found, based on the best cumulative Q^2.

Table III. Results for partial least squares (PLS) models generated from refining line data, with different hours excluded.

Data Pretreatment Step	Number of Hours Removed
Low production periods, based on *minimum* throughput	90
PCA outliers, based on score plot	6
PCA outliers, based on distance-to-model plot	32
One-hour periods retained for partial least squares (PLS) model	641
TOTAL	768

Table IV. Hours retained and removed for August 2003.

Table IV summarizes the final tally of hours retained and hours removed for August 2003, out of the original 768 one-hour periods.

FILTERING NOISE

Figure 3 shows plots of the original primary and secondary motor loads for August 2003, overlaid by the filtered signals for two different values of alpha in EWMA. (Alpha is the weighting, between zero and one, given to the previous value in the sequence. The weighting of the current value is one-minus-alpha. An alpha of zero means there is no filtering.)

The lower value of 0.5 was the point at which smoothing started to become visibly apparent on the plots. The upper value of 0.8 was chosen because it yielded the smoothed curve that fit the original data the best, admittedly a somewhat subjective evaluation. At alpha values above 0.9, the curves became visibly overfitted. Note that with an extreme alpha (> 0.99), all signals begin to resemble a straight line.

At an alpha of 0.8 there is a noticeable shift of the raw data to the right, caused by the inertia of the moving average. Plotting the cross-correlation curves for filtered versus unfiltered data showed this shift to be about 2 hours. However, since this shift applies equally to all variables—both X and Y—the accuracy of the model should not be affected. Obviously this shift would have to be taken into account if filtered and unfiltered signals were used in combination.

Table V shows the results of the various PLS models for August 2003. The combined Q^2 value for the three dependent variables (freeness, fiber length, and fines) is shown are for a model with four components. In all cases, components numbered 5 and above contributed little or no incremental gain to the overall goodness of fit, and may therefore represent random noise in the data. The improvement in goodness of fit when EWMA is applied is striking, with a jump in Q^2 from 41% to 61% just by using an

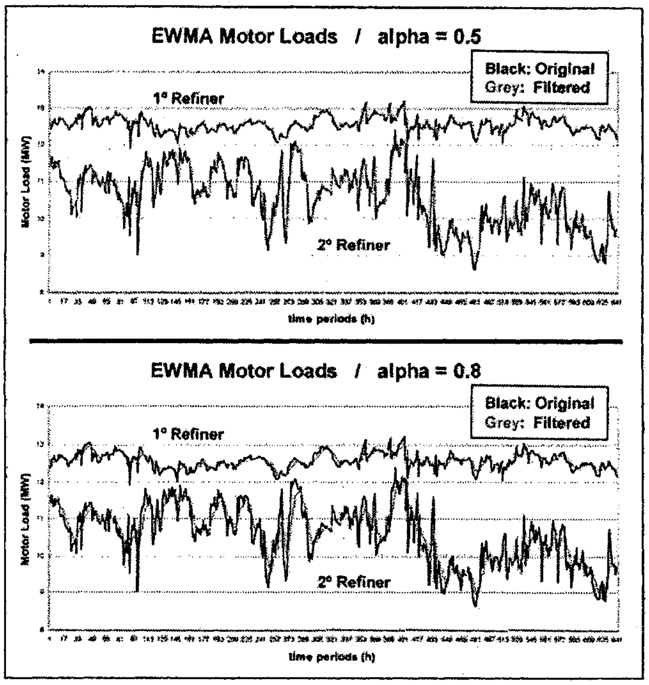

Figure 3. Filtered vs. original motor load signals for August 2003, showing smoothing effect of exponentially weighted moving average at different alpha values.

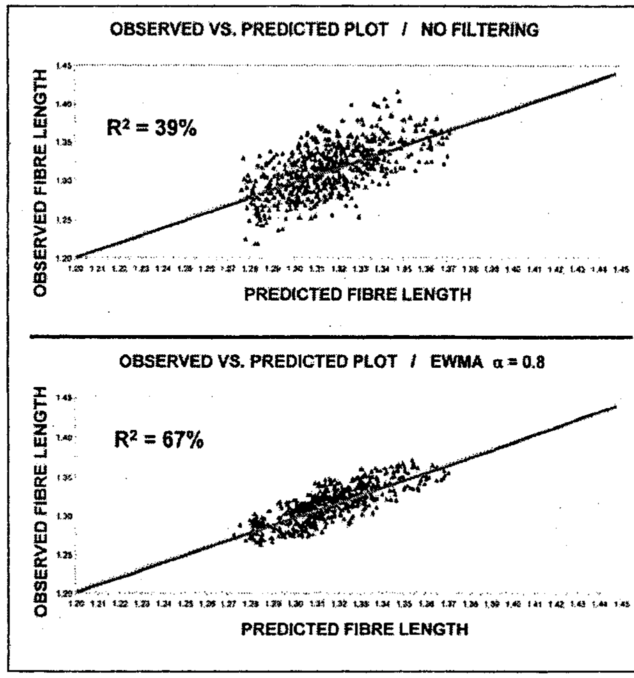

Figure 4. Observed vs. predicted plots for fiber length in the partial least squares (PLS) model, using different filtering methods, August 2003 (diagonal is 1:1 line). The R^2 value is that calculated by the PLS model.

alpha of 0.8.

The trimming/winsorizing step entailed the removal of the top and bottom 1% of values for each individual variable, and their replacement with the value at the cut-off point. This option had little effect on the results. This was not surprising. Intuitively this method does not seem suited to time series data, where the most extreme values might be due to process shifts and not aberrant measurements.

The improvement in accuracy with filtering is apparent in Fig. 4, which shows the observed vs. predicted plots generated for average pulp fiber length. The two plots show the data clouds with and without EWMA for August 2003.

Table VI indicates possible interpretations for the components for August 2003. These are based largely on which X and Y variables showed the largest PLS loadings, i.e., the weights assigned to each original variable by the PLS model. The larger the loading, the more that term contributed to the PLS model. Motor loads and dilution flow rates are often highly correlated with production rate. For PCA modeling, this could be a pitfall. This one dominant trend could eclipse other, more interesting correlations. However, when using a PLS model, it is acceptable to have highly correlated variables among the Xs, because a component in the X space can only contribute to the PLS model if it correlates with a trend among the Ys, regardless of the number of underlying variables.

Conditions at the primary refiner seem to mostly correlate with pulp freeness, whereas conditions at the secondary refiner more closely relate to fiber length and fines. This is consistent with discussions we have had with the TMP operators at the mill and with equipment suppliers. Similar components were found when the data were filtered, suggesting that the overall correlational structure of the dataset was not compromised by using EWMA.

Filtering option	Overall Q^2	# of Comp.[1]
No filtering	40.63%	4
Trim / winsorize	40.56%	4
EWMA, α =0.5	50.13%	3
EWMA, α =0.8	60.75%	2

[1]The column titled "# of Comp." indicates the number of components required to achieve an overall cumulative Q^2 equivalent to that of the "no filtering" case.
EWMA = exponentially weighted moving average.

Table V. Comparison of partial least squares (PLS) results for different data filtering methods.

Note that freeness is logarithmic with almost any other variable. However, in a previous study [12], we replaced freeness with its logarithm and obtained exactly the same PLS models. The most likely explanation is that within our dataset the freeness only varied between 200 mL and 250 mL, which is too small a range for the nonlinearity to show itself. We therefore used the original freeness values.

Table VII compares results for the four different months studied. Compared to the August 2003 base case, March of that year showed a large number of start-ups and shutdowns, with over a third of the hours being identified for removal. The final PLS model was much weaker than for August, possibly related to greater variability in incoming chip quality (typically not well measured at Canadian newsprint mills). Again, the overall Q^2 was significantly improved by using EWMA. Furthermore, the prominent X variables for March were different for August, with the first component being dominated by low specific energy in the primary refiner, which the TMP operators often associate with lower quality chips.

Apart from the fact that the models were stronger, the 2004 findings were similar to those of 2003. However, once again, which X variables were prominent differed from one month to the other. The process clearly evolves over time, such that no two months have exactly the same coefficients. Using MVA for advanced control would therefore require some kind of adaptive controller, as reported by other authors [3].

#	Variables with Highest PLS Loadings[1]	Possible Interpretation of Component
1	X: 2° motor load (-) Y: freeness (+), fiber length (+), fines (-)	Impact of 2° refining energy on fiber length
2	X: 2° plate gaps (+), 2° steam P (-) Y: fiber length (+), fines (-)	Older plates requiring tighter gap in 2° refiner, yielding shorter fibers and more fines
3	X: 2° dilution (+), 1° plate gaps (+) 1° motor load (-) Y: freeness (+)	Lower primary refining energy, yield ing higher freeness
4	X: 2° steam P (+), 2° conical plate gap (-) Y: fiber length (-), fines (+)	Higher refining intensity in secondary refiner, cutting fibers, and generating fines

[1]The parentheses show whether the loading was positive or negative, which indicates either a positive or a negative correlation *vis-à-vis* the other variables. Caution must be exercised when assigning cause-and-effect relationships to purely statistical outputs.

Table VI. Interpretation of partial least squares (PLS) components for August 2003 mill data.

		Overall Q2		
Month	Hours Removed	No Filtering	EWMA ± = 0.8	Dominant X Variables
March 2003	273 out of 768 (36%)	23%	38%	1° energy, 1° dilution, 1° plate gaps
August 2003	128 out of 768 (17%)	41%	61%	1° and 2° energy, 2° plate gaps, 2° steam P
March 2004[1]	258 out of 768 (34%)	56%	67%	2° energy, 1° plate gaps, 1° and 2° consistency
August 2004	170 out of 768 (22%)	59%	68%	1° and 2° energy, 1° dilution, 1° and 2° consistency

[1]Maintenance on the PulpExpert unit during this month may have affected results.
EWMA = exponentially weighted moving average.

Table VII. Partial least squares (PLS) results for different months using identical variables and data pretreatment.

RECOMMENDATIONS

The main focus of this paper was to examine, in a systematic way, various techniques for preselecting and pretreating TMP process data to increase the realism and usefulness of PLS black-box models for pulp quality. For the purpose of this study, pulp freeness, average fiber length, and fines content at the latency chest were combined into a single statistical model. The models were compared on the basis of pure statistics, notably goodness-of-fit, and on model interpretability. Significantly better PLS models were obtained when mill data were pretreated as follows:

1. Low-production periods were stringently removed so that no second-by-second data point during the entire hour fell below the threshold.
2. PCA outliers on both the score and distance-to-model plot were removed using Hotelling's T^2 (95-percentile).
3. Aggressive EWMA filtering was applied to all Xs and Ys.

While data pretreatment is clearly essential to successful application of MVA, these methods are generally compromises, with no one single "best" data pretreatment methodology. However, in our study the models using pretreated data were better, whether evaluated using statistical metrics or qualitative tests.

One possible explanation for the success of filtering is that MVA is normally blind to time series data, treating all data points the same regardless of how far apart they are in real time. Filtering with EWMA essentially overlays time-related information onto the dataset, introducing a dynamic element not present in the original unfiltered data. By providing the algorithm with more information about the system, filtering improves its ability to find correlations between the dependent and independent variables. EWMA did not appear to affect which X and Y variables were most prominent, suggesting that even with a high level of filtering, the model was still representative of the original data.

PLS outputs must be studied carefully to ensure that the results correspond to the known properties of the system. The PLS models from this study were consistent with expected results, such as lower specific energy being associated with less fiber development (higher freeness) and less fiber cutting (longer fiber length and lower fines). Another observed effect was plate age. However, caution must be exercised before ascribing cause-and-effect to what are purely statistical outputs, since both the Xs and the

Ys might simply be responding together to an outside influence.

Different X variables were prominent from one month to the other. It would appear that the process evolves over time, such that no two months will yield exactly the same model, even if the list of key parameters remains constant. Unmeasured fluctuations in incoming chip quality is one plausible explanation, though without better data this remains conjecture. Using MVA for advanced control would therefore require an adaptive controller, in which the variables remain the same but the coefficients are continually updated.

Even our best models only explained 40% to 60% of the variance in the Y parameters, meaning that about half of the variance corresponds to unmeasured variables. The various on-line woodchip monitors under development should help to address this data gap. **TJ**

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INSIGHTS FROM THE AUTHORS

Many mills are faced with the problem of data overload. With this work, we're trying to help them extract useful information from these large databases to address product quality issues. Until now, we have focused on selecting which variables to use and on interpreting the multivariate analysis (MVA) results to have physical meaning. This was the first time we systematically applied different data pretreatment techniques to see which ones gave the best model of thermomechanical pulp (TMP) quality.

The most difficult aspect of this work is problems with the data. No matter how much we understand the process and focus on the right variables in the right combinations, there is no guarantee that this type of black box modeling will actually yield any useful results. We addressed this challenge by studying the data beforehand, with simple time plots for each variable, to make sure we were weren't just modeling instrument drift or calibration or other nonprocess trends.

The next step is to model all four TMP lines together, for overall pulp quality. What I discovered personally from this research is that sometimes it is only a small number of datapoints that "spoil the barrel." By eliminating these, we can greatly improve the accuracy and usefulness of the MVA models. The most surprising thing is that when things go well, you really can model a portion of the variability in pulp quality by using the TMP operating parameters.

Harrison *Stuart*

All mills have product quality fluctuations they would like to be able to explain better. They have large amounts of operating data, but it is difficult to sift out any useful trends from the rest.

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APPENDIX IX:

International Peer-Reviewed Publication – 2007 – Tappi Journal

IMPACT OF TMP REFINING LINE INTERRUPTIONS AND REJECT REFINER OPERATIONS ON PULP AND PAPER VARIABILITY

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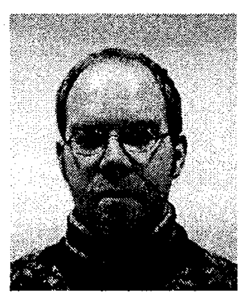

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APPLICATION STATEMENT

This study presents a straightforward method for combining individual TMP operations, including reject refining, into a single statistical model for explaining quality fluctuations in pulp and final newsprint.

SUMMARY

Modern TMP newsprint mills face the double challenge of varying chip quality, and an increasingly demanding clientele who expect better and more consistent product. This article develops a method for correlating TMP operations with pulp and, ultimately, paper quality by focusing on process fundamentals such as specific energy and refining intensity. The case study is an Eastern Canadian newsprint mill which experiences variability in paper strength and porosity. Frequent interruptions in the four refining lines greatly affect the reject specific energy and other key parameters, many of which are not measured directly and must be calculated from other variables. Due to the infrequency of measurements, linking paper variations to upstream pulp quality variables such as freeness, fiber length and fines content is difficult. However, the mainline refining and reject sections are data rich, with many parameters measured second-by-second. Using Multivariate Analysis and other statistical tools, it was possible to link pulp quality back to TMP and rejects operations, taking into account number of lines in operation, plate age and process lags. Furthermore, it was possible using MVA models to correlate roughly half of the variability in final paper quality with the refining operations. One conclusion of this work is that even better results would likely be obtained with more on-line measurements, notably for incoming chip quality and reject refining consistency.

CAPTIONS FOR IMAGES (SEE ATTACHED JPEG FILES)

Figure 1: Power spectrum for tear strength, generated from hourly measurements over one month (August 2004).

Figure 2: Statistical relationship between specific reject refining energy (calculated from other variables) and pulp quality at the refined rejects outlet. 2a) bivariate plot, showing the cross-correlation between reject specific energy and fiber length, August 2003. 2b) corresponding multivariate 'loadings' plot showing all the reject variables.

Figure 3: Structure of PLS model showing independent (X) and dependent (Y) variables. No useable data were found for chip quality.

Introduction

Canadian TMP newsprint mills currently face a double challenge – varying chip quality, and an increasingly demanding clientele who expect better and more consistent product. Companies are now less vertically integrated, and have less direct control over the wood supply. Many chips are now coming from outside sawmills, where they are seen as a secondary by-product, with little or no attention paid to quality assurance. Unfortunately, many existing TMP mills have built-in characteristics, such as limited chip storage, that make final newsprint quality highly susceptible to disturbances. This situation only exacerbates other economic factors that are making it increasingly difficult for North American newsprint mills to compete internationally.

To achieve more consistent paper quality, we must reduce the variability in the intermediate pulp. Mills have certain expectations of productivity, however, and seek to maximize overall equipment efficiency. Many mills therefore operate at or above nominal capacity virtually all the time, leaving little or no 'wiggle' room to compensate for outside disturbances.

At the same time, mills are faced with yet another new challenge, namely a glut of process data captured by millwide data historians. While theoretically this is a gold mine of information on the inner workings of the different unit operations, in practice it is often difficult to show trends and relationships connecting the different sections of the mill. Missing, sparse and/or poor measurements are partly to blame, but another equally important reason is the multivariate nature of the TMP mill itself.

Studying one or two variables at a time is a fruitless task, because the operating parameters, pulp measurements and final paper quality are connected in such a way that the interactions between them are as important as the variables themselves. To be properly understood, therefore, the different variables in a TMP mill must be studied in combination. One method for doing this is the statistical technique known as Multivariate Analysis, or MVA. Like all so-called "black-box" methods, which rely only on inputs and outputs, it has the pitfall of blindly attributing correlations between variables without any regard whatsoever for the actual underlying process.

Our goal was not to create a universal predictive model of the TMP process, which is virtually impossible without planned experiments. Rather, the objective of our research is to develop a methodology for identifying the probable main sources of variation in important paper parameters, using routinely collected data. This article presents part of the solution, by proposing a way to correlate TMP operations with pulp and, ultimately, paper quality via process fundamentals such as specific energy and refining intensity. The case study is an Eastern Canadian newsprint mill which experiences short- and long-term variations on the order of ±10-15% in final paper strength. Discrete events like primary/secondary refining line interruptions, and changes in reject refiner operation, are an integral part of this case study.

Rich vs. Poor Data Sources

The impacts of pulp characteristics on final paper quality are well established. Newsprint strength, for instance, is known to depend on pulp fiber length, while other parameters critical to paper quality include freeness and fines content [1,2,3]. When using real mill data, however, it is often a challenge to show these links statistically due to the infrequency of measurements. Longer-term variations can be shown, such as weekly or monthly averages [4], but at shorter timescales the correlations are much harder to demonstrate.

This is true of the case study mill, whose characteristics were described in an earlier paper [5]. Pulp samples at the mill are automatically analyzed roughly every 60-120 minutes, as shown in Table I. The sampling itself only lasts some 30 seconds, so these are grab samples and not composite samples. Along with the inevitable measurement error and calibration issues, this tends to create much variability from one reading to the next. Moreover, pulp is a highly complex mix of organic compounds, both cellulosic and non-cellulosic, with a biological origin. It therefore cannot possibly be fully characterized by a handful of infrequent, macroscopic measurements.

One goal would be to automate the control of the TMP refiners to achieve the required pulp quality. Data from the papermaking section (longer loop) could be used to update the setpoints for pulp quality (shorter loop), as has been proposed in several commercial applications [6]. Before doing this, however, it is necessary to understand the impact of TMP operations on pulp and paper variability. The variables used in this study are shown in Table II and Figure 3.

In contrast to the pulp, for paper the number of variables tested automatically is much higher, and there is a certain degree of redundancy among the numerous strength tests. However, measurements are still relatively infrequent. Tests are performed on a 30-cm wide strip at the end of each reel, again a small grab sample, corresponding to a period of roughly every 45 minutes. For the purposes of this study, the following paper parameters were used: tear strength, burst strength, tensile stiffness index, and permeability to air (an indicator of porosity). These were selected based on preoccupations at the case study mill, and known relationships with the parameters tested in the pulp.

Sparser still are measurements on the incoming chips, tiny grab samples which are taken from the main conveyor belt only every eight hours. Furthermore, the tests performed on the chips are limited to density and moisture measurements, a rough size distribution, and rot content. Apart from very long term trends, such as season-to-season, these chip data are far too limited to be useful for predicting final paper quality. Better and more frequent measurement of the chips would likely be extremely helpful, given the importance of wood species, growing conditions, harvesting techniques and other factors on final paper quality [7,8].

In stark contrast, the mainline refining and reject sections are extremely rich in frequent, plentiful data. The refiners and ancillary equipment are highly instrumented, with many operating parameters measured continuously. Fast variables, such as motor load, are logged in the data historian once per second, providing a very large amount of process information. However, these data present some important challenges:

- Certain critical operating parameters go unmeasured, e.g., refining consistency.
- Variables are not in a form corresponding to known process fundamentals.
- Measurements are subject to instrument drift and calibration problems.
- Frequent start/stop of refiners.
- Gradual effect of equipment wear, such as plate age.
- Presence of process lags.

Some of these issues, like instrument drift and equipment wear, are true of any TMP mill. Others, like lack of refining consistency measurement, are specific to the case study mill.

Another particularity of the case study mill is overcapacity in the pulp section relative to the paper section. This results in frequent interruptions in each of the four main refining lines, which greatly affects the reject refining specific energy and other key parameters. A method for dealing with this problem is proposed below.

Despite these issues, it should be possible to exploit the richness of the refining data to model pulp and newsprint quality. First, though, we must determine if the sampling frequency of the final paper is sufficient to be useable for MVA.

Frequency of Paper Sampling

As mentioned above, the final paper quality is tested using small strips at the end of each reel. This is unavoidable, because newsprint is sold in long continuous sheets, which would be destroyed by intermittent cutting. This means, by definition, that any MVA models constructed using these data will at best be linked to long-term fluctuations in paper quality, as opposed to shorter-term fluctuations such as would occur within a single reel. The question remains whether these measurements properly represent long-term variations in paper quality, or have been corrupted by the presence of short-term variations – the problem of aliasing. In other words, the question is whether the long-term paper quality variations (e.g., of period greater than 2 hours) are sufficiently large compared to the short-term variations (e.g., less than 2 hours) to allow one-hour sampling to properly track the majority of quality variations.

Following the technique recommended by Croteau *et al* [9], we studied the power spectra of all the paper characteristics of interest, using one-hour averages. We found that three-quarters of the variability occurred at a frequency below 0.1 cycles per hour, i.e., at a time constant above 10 hours. Over 95% of the variability was below 0.4 cycles per hour, i.e., longer than 2.5 hours. This would suggest that the slower trends in final paper quality are indeed adequately represented, and that this sampling frequency is sufficient for our purposes. Figure 1 shows the power spectrum for tear strength only, but similar plots were found for all the paper parameters under study. There are two reasons for the long-term nature of these variations: the process, with its numerous tanks, screens and recirculation loops, acts as a filter for the pulp quality variations; and, control loops at the paper machines tend to stabilize the short-term fluctuations in basis weight, moisture and caliper that would affect other paper properties.

It may seem paradoxical to use one-hour data to justify a one-hour time increment. Had we been doing planned experiments, rather than using pre-existing data, no doubt we would have selected a shorter sampling frequency, to be more conservative. However, such are the limitations when using real operating data.

Integrating TMP Fundamentals into PLS Model

The main variant of MVA used to relate independent (X) variables to dependent (Y) variables is known as Partial Least Squares, or PLS. As with any purely statistical method, without the use of a designed experiment no causality can be inferred, just correlation.

MVA is a purely statistical tool, and is automatically drawn to the most prominent trends in any dataset. Starts and stops of equipment, setpoint adjustments, routine calibration and other abrupt shifts will tend to dominate the latent variables, or "principal components", that are generated by the MVA algorithm. It is therefore necessary to pre-treat raw process data before using MVA, if only to remove periods of low production and other outliers, and filter out noise. A detailed methodology for pre-treating TMP operating data was presented in an earlier TAPPI article [5].

Because MVA is a linear technique, it is also necessary to modify the variables to correspond better to the underlying process. TMP refiner operation is dominated by two non-linear terms, namely specific energy, defined as mechanical energy per metric tonne of pulp produced, and refining intensity, or the specific energy per bar impact. Both must be properly controlled to ensure good pulp quality.

Specific energy is the central parameter of refiner operation. It must be high enough to ensure fiber separation and defibrillation, but low enough to avoid excessive fiber cutting which can adversely impact the strength of the final paper [10]. Specific energy is not controlled directly, but rather indirectly via the manipulated variables of throughput, dilution flow and plate gap. It is relatively easy to calculate, since motor load is very accurately measured. Production rate is known from the volumetric feedrate, although the latter is susceptible to fluctuations in chip density.

Refining intensity is much more difficult to measure in an industrial refiner. It indicates *how* the mechanical energy is applied, whether gradually over a large number of bar impacts, or suddenly by just one or two jarring impacts. The latter situation is highly damaging to fibers [11,12,13]. For a given plate configuration and disc rotation speed, refining intensity is largely a function of refining consistency [10]. This is an inverse relationship: higher consistency means a longer fiber residence time between the refiner plates, and hence more bar impacts of lower refining intensity for a given specific energy. At the case study mill, refining consistency is not measured directly in real time, but for Line 1 an on-line calculation is made available to operators based on a simple mass/energy balance. By comparing the equation in the DCS logbook to real production data, it was possible to deduce the coefficients and extend this calculation to the other three lines.

The refiner plates have a normal lifespan of about 2000 hours, during which time the bars on the plate surface are gradually worn down, affecting the process characteristics. Less energy is required with an older plate to achieve a given freeness, but the refining intensity is higher because the plate gap is smaller, resulting in more damaged fibers [9]. Lama *et al* [14] reported the effect of plate age on a mathematical model of TMP motor load for a twin refiner. Plate age displays both slow and very fast effects on the TMP refining process, because the plates wear down gradually over several thousand hours of operation, and then are abruptly replaced with new plates. At the case study mill, the individual plate ages are continuously logged in the data historian, and so are readily available.

Importance of Reject Refining

A very important, and sometimes overlooked, part of any TMP mill is reject refining. Because the case study mill experiences frequent starts and stops on the four main refining lines, the throughput at the presses, and ultimately the reject refiners, is continually changing. Partly to compensate for this, the operators tend to increase the reject rate from roughly 30% to 40% after a line stoppage, meaning that the fiber length distribution of the pulp entering the reject refiners varies over time. These adjustments are made manually and not automatically, and there tends to be a lag of several hours. Combined with occasional stoppages of the reject refiners themselves, this situation results in a highly variable and poorly controlled reject refining.

Unfortunately, the measurements at the reject refiners are insufficient to calculate the consistency, which could serve as an indicator of reject refining intensity. However, it is possible to calculate the specific energy at the reject refiners, by adding the motor loads of the two reject refiners (they operate in parallel) and dividing by the throughput. The latter was estimated by simply multiplying the reject rate by the total production of the four main lines. The specific reject refining energy thus calculated showed a very large variability from hour to hour, ranging from 800 kWh/t to over 1400 kWh/t. By looking at the original variables, we concluded that this variability was due to fluctuations in both the numerator (motor load) and the denominator (throughput). Sometimes one of the two reject refiners was stopped, but the number of reject refiners in operation was not always a function of the number of working TMP lines.

Though based on several assumptions, this estimate of specific reject refining energy showed significant correlation with the pulp quality at the refined rejects outlet, much more so than the original variables did. This was true for both bivariate (cross-correlation) and multivariate (MVA) statistical tests, as shown in Figure 2 for fiber length. Note that the calculated specific reject refining energy dominates the MVA plot in 2b (second column from the right) despite the presence of the original variables from which it had been calculated.

In each case, the amount of variability explained is not particularly high: a correlation coefficient of 31% in one case, and a Q^2 of 14.5% in the other (Q^2 represents the proportion of the Y variance captured by the PLS model; it is similar to R^2 but decreases with overfitting). This is not surprising, since reject refining is only part of the overall picture. The point is that these correlations, while only explaining part of the picture, are nonetheless statistically significant as indicated by the 95% confidence limits on both plots.

Process Lags

MVA is not a time series technique, and treats all observations exactly the same, whether they be sequential or three weeks apart. Process lags must be synchronized beforehand, otherwise the algorithm will blindly combine data for different moments in time into a series of muddled, meaningless datapoints. At the case study mill, the process lags for the mainline pulp are not constant because of changes in tank levels. However, for the purposes of this study the monthly average lags between unit operations were used. These can be estimated by comparing cross-correlation curves [15], in this case for fiber length measured at different points in the process, as listed in Table III.

An attempt was made to link process lags to High Density tank levels, which tend to fluctuate significantly. However, no statistically significant relationships could be found, probably due to the small number of datapoints available for any given tank level.

Linking Paper Quality Back to TMP Operations

To model the final paper quality, it was necessary to combine all the different TMP sections into a single model. Essentially, we did to the data what occurs to the pulp within the real process, i.e., combine all the main lines as well as the reject lines, add process lags, and dampen high-frequency fluctuations.

Initially, we created models in which the four TMP lines appeared separately. It quickly became apparent that this approach led to serious problems. The models were exceptionally hard to interpret, because they tended to reflect the idiosyncrasies of the four individual lines, rather than the entire upstream effect on the pulp and newsprint. Thus, one week Line 1 might dominate, whereas for a different week it might be Line 3. Not surprisingly, these models tended to be weaker overall.

Before combining the four main TMP lines, each was first treated individually by removing all shutdown periods. Any hour during which the minimum production rate (i.e., smallest second-by-second value over the entire hour) was below 200 t/d was systematically erased. The hour itself was not removed, but the values for production, specific energy and consistency were replaced with blanks. Combining the four main lines, therefore, consisted in taking the average of just those lines that were in operation for any given hour. This technique completely eliminated the effect of starts and stops, while giving the correct weighting to the lines in operation.

In the case of plate age this approach was unnecessary, because the plates do not age when the line is shut down. The ages for all four lines were simply added together. In order to differentiate between the different kinds of refiners, the four primary refiners were considered as one group, the four secondary refiners as another group, and the two reject refiners as a third group. These total plate ages were then used as new X's in the MVA model, to give the final choice of X's listed in Table II.

Due to frequent grade changes, the original plots of the tear and bursting strengths showed abrupt shifts not related to the upstream TMP process. This would have destroyed any chance of linking these two parameters to the refining section Dividing these two parameters by the basis weight, to create an index, greatly reduced this effect, underlining the importance of studying the original data before doing any MVA. Permeability was also clearly linked to basis weight, but in this case indexing was not helpful so the models were limited to periods of 45-g/m^2 production (roughly two-thirds of the hours) for this parameter only.

All variables, both X and Y, were further treated to remove outliers and noise. Using another variant of MVA known as Principal Component Analysis (PCA), we identified datapoints that did not fit the overall correlational structure. Often these outliers yield interesting clues about the process, such as shifts in operating regime. In this case, however, our goal was to represent the most typical TMP operation and relate it to slower trends in the paper, so the outliers were systematically removed. To counter noise, all variables were also subjected to filtering. We used an exponentially weighted moving average (EWMA) with an alpha value of 0.8, corresponding to a first-order filter with a time constant of 4 hours – a rough approximation of the filtering of the process.

Using this approach, it was possible to link pulp quality back to the TMP operations, including the reject refining, as shown in Table IV. The Q^2 value listed is a combined metric for that group of dependent variables; the results obtained would be different if each dependent variable had been modelled separately. Table V shows the TMP and reject operating variables associated with each of the dependent variables, in other words which X variables were grouped by the PLS model with the Y variables. For the most part, the trends that we found correspond to what would be expected for a typical TMP operation.

Using this multivariate approach, we were also able to find correlations between the upstream operations and the final newsprint. Table VI shows which TMP and reject operating variables were statistically linked to each of the paper quality parameters. Again, the results are consistent with expectations. One interesting result not reflected in the table is the presence of a link between secondary plate age and strength (positive) and permeability (negative), exactly the opposite of the other two plate ages. This could be attributable to coincidence, or to some outside factor affecting the process. Again, it is important to highlight that MVA only finds correlation, not causality.

It is important to note that the Q^2 values presented above represent the proportion of the Y variance captured by the model, and not the statistical significance of the model *per se*. The latter is indicated by the 95% confidence limits on the PLS histograms. When using real process data, it is common to have Q^2 values in the range of 40%, i.e., the model explains with statistical significance 40% of the Y variance. The unexplained portion of the variance corresponds to unmeasured (or unmeasurable) process variables that impact the quality parameters, or to measurement errors and noise, both of which are prominent in real operating data.

Discussion

Using historical TMP operating data, while a promising source of insight, can be difficult due to outliers, noise, and the multivariate nature of the process itself. MVA is a cheap, non-intrusive method for treating such data, although interpreting the results and avoiding findings that are merely coincidental can be quite difficult.

Using MVA and other statistical tools, it was possible to link one-hour values for pulp freeness, fiber length and fines content back to the TMP refining operations, including reject refining. To get the best results, it was necessary to convert the existing variables into a form closer to the process fundamentals by creating non-linear terms to represent specific energy and refining intensity. It was also necessary to take into account number of lines in operation at any given time, the gradual wearing of the refining plates, and process lags. Of all these factors, plate age seemed to have the greatest effect on pulp parameters, even though actual plate wear is known to be non-linear with time. Specific energy at the reject refiners also had a significant effect, notably on fiber length.

Refining consistency, calculated from other variables, was found to trend almost always with specific energy. As a result, the anticipated independence of specific energy and refining intensity was not observed. To verify this point, it would be necessary to conduct planned experiments in which specific energy is held constant, and the refining consistency is manipulated in a controlled manner.

With the same approach, it was also possible to explain roughly half of the variability in final paper quality, in this case strength, porosity and linting. This is quite remarkable, considering that no paper machine operating variables were used, and that little or no data were available on incoming chip quality. Of course, these results are correlational and not cause-and effect; it is possible that both the TMP operations and the paper are being affected by a third, unmeasured factor. This question will be the theme of our next article, along with a systematic comparison of different timescales and sampling locations.

Such an approach could be used for a two-tiered control strategy, where paper monitoring results serve to update setpoints for pulp quality at the TMP section. Because the TMP process is a moving target, any such strategy would require an adaptive controller.

Recommendations

Using Multivariate Analysis and other statistical tools, it was possible to link pulp quality back to TMP and rejects operations, taking into account number of lines in operation, plate age and process lags. Furthermore, it was possible to explain roughly half of the variability in final paper quality by creating MVA models of the refining operations based on process fundamentals such as specific energy and refining intensity. Based on our results, it seems there is room for improvement in the control of specific energy and the scheduling of plate changes. Another conclusion of this work is that even better results would be likely obtained with more on-line measurements, notably for incoming chip quality and reject refining consistency.

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Table I. Rich vs. Poor Data Sources at Case Study Mill.

Data Source	Frequency of Measurement	Number of Variables	Richness of Data
Wood chip quality	Grab sample every 8 h	A few physical characteristics	Very poor
TMP mainline operation	Once per second	Large number of energy, pressure and flowrate measurements	Rich
Reject refiner operation	Once per second	Some key variables missing; must be calculated	Rich
Pulp quality – latency chest	Grab sample every 60-120 min	Limited to freeness, fibre length and fines	Poor
Pulp quality – stock prep.	Grab sample every 60-120 min	Limited to freeness, fibre length and fines	Poor
Final paper quality	Grab sample every 45 min	Many variables with much redundancy, esp. for paper strength	Intermediate

Table II. Variables used to generate PLS model of TMP mill.

Variable	Unit
X-Variables	
Production rate (proportional to feed screw rotational speed)	t/d
Number of TMP lines in operation	–
1° & 2° specific refining energy	kWh/t
1° & 2° blowline consistency (calculated with simple mass/energy balance)	% solids
1° & 2° plate age	h
Standard deviation of motor loads (1° & 2°)	MW
Reject refining specific energy	kWh/t
Reject plate age	h
Y-Variables – Pulp Properties (PulpExpert)	
Canadian Standard Freeness	mL
Average fiber length (length-weighted)	mm
Fines content, defined as small enough to pass through 200 mesh screen (76 μm)	% (mass)
Y-Variables – Paper Properties (Autoline)	
Tear MD (index)	$mN/(g/m^2)$
Tear CD (index)	$mN/(g/m^2)$
Bursting strength (index)	$kPa/(g/m^2)$
TSI MD	kNm/g
TSI CD	kNm/g
Permeability to air (indicative of porosity)	mL/min

Table III. Average process lags used in PLS model, based on cross-correlation curves for average fiber length at various locations, for August 2003.

Location	Lag
Based on cross-correlation curves:	
Headbox feeder tank	0 h
Disk filter feed	-2 h
Refined rejects outlet	-3 h
Primary screen accepts	-5 h
Outlet of latency chests	-5 h
Assumptions, by simple extrapolation:	
Final paper	0 h
Reject refiners	-5 h
Primary and secondary refiners	-6 h

Table IV. Summary of PLS models obtained using hourly averages for month of August 2003.

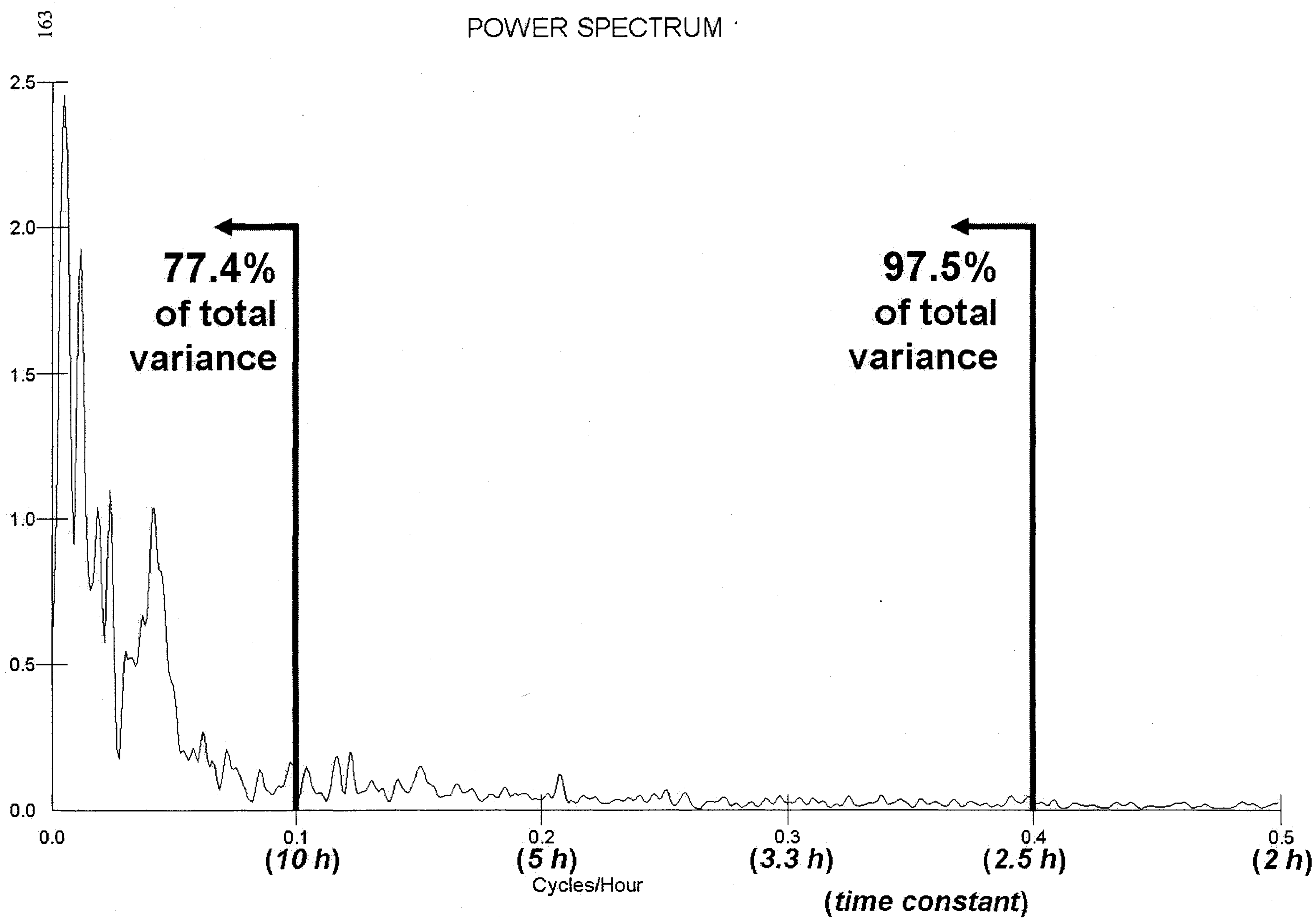
PLS Model	Number of Components	Q^2
Pulp Quality (freeness, fiber length & fines content)	5	38%
Paper Strength (tear, burst & TSI)	3	47%
Porosity (permeability to air)	3	69%

Table V. Pulp Quality Model – TMP and reject refiner operating variables (X variables) most associated with each dependent (Y) variable. August 2003.

Sampling location	Dependent (Y) variable	Independent (X) variables showing strongest correlation within PLS model
Outlet of refined rejects tank	Higher freeness	Lower specific energy in reject refiners.
	Higher average fiber length	Lower overall specific energy; lower refining consistency; older plates.
	Higher fines content	Higher overall specific energy; higher refining consistency; newer plates; fewer TMP lines in operation; higher motor load standard deviation.
Primary screen accepts	Higher freeness	Lower overall specific energy; lower refining consistency; older plates.
	Higher average fiber length	Lower overall specific energy; lower refining consistency; older plates.
	Higher fines content	Higher overall specific energy; higher refining consistency; newer plates; fewer TMP lines in operation; higher motor load standard deviation.

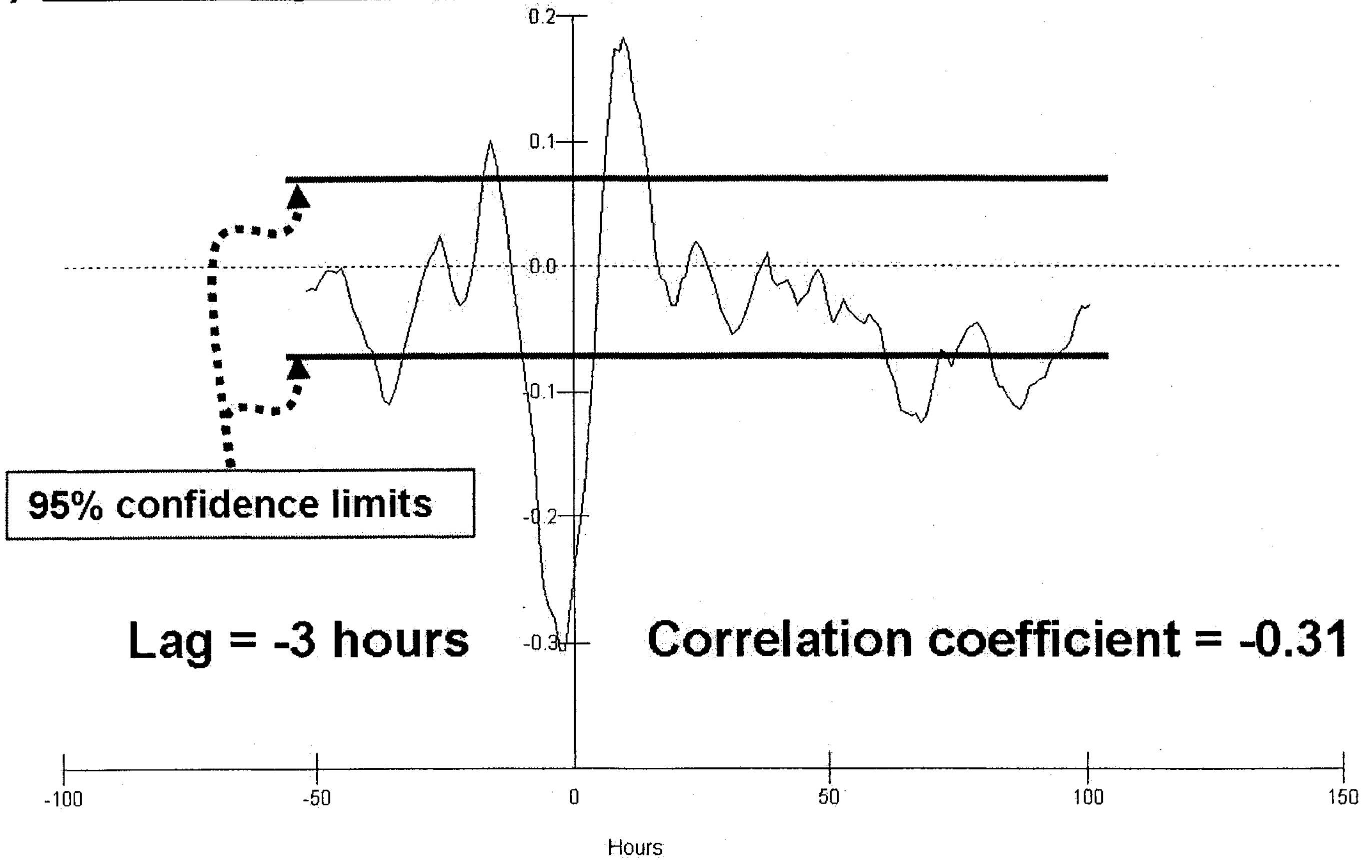
Table VI. Paper Quality Model – TMP and reject refiner operating variables (X variables) most associated with each dependent (Y) variable. August 2003.

Dependent (Y) variable	Independent (X) variables showing strongest correlation within PLS model
Higher tear strength	Higher overall specific energy; higher refining consistency; newer plates; more TMP lines in operation.
Higher bursting strength	Higher overall specific energy; higher refining consistency; newer plates; more TMP lines in operation.
Higher TSI	Higher overall specific energy; higher refining consistency; newer plates; fewer TMP lines in operation.
Higher porosity (permeability to air)	Lower overall specific energy, esp. at reject refining; lower refining consistency; older plates; more TMP lines in operation.

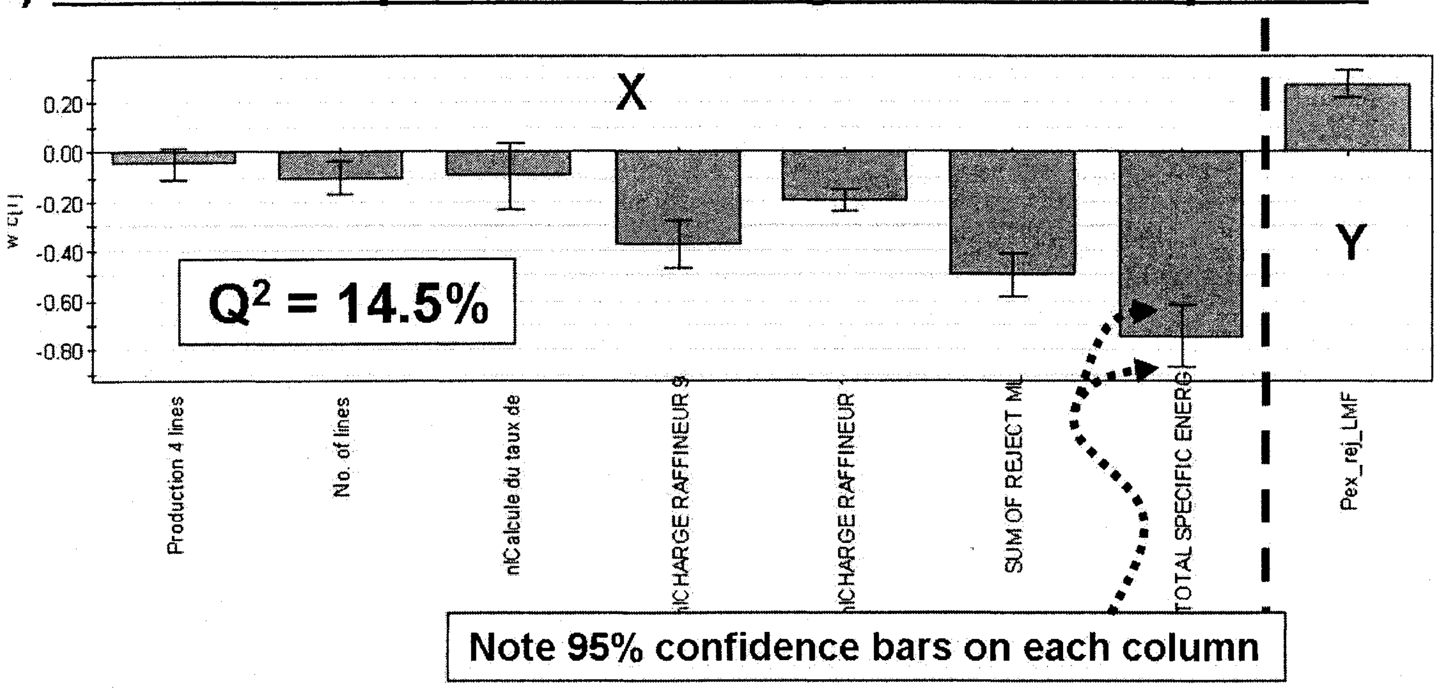


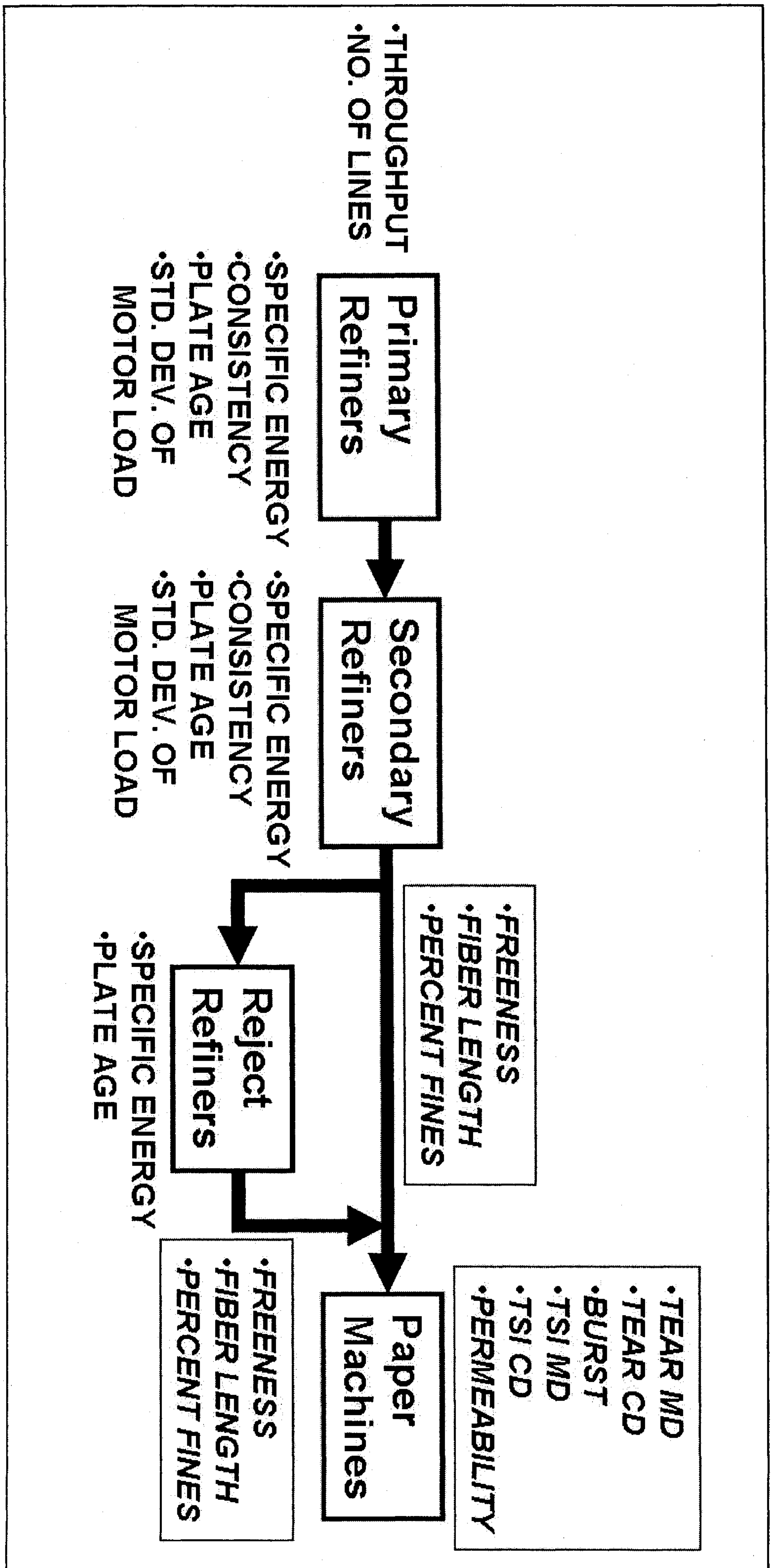
POWER SPECTRUM
2.5
2.0
1.5
1.0
0.5
0.0
77.4%
of total
variance
97.5%
of total
variance
0.0
0.1
(10 h)
0.2
(5 h)
0.3
(3.3 h)
0.4
(2.5 h)
0.5
(2 h)
Cycles/Hour
(time constant)

) Bivariate plot: Cross-correlation



) Multivariate plot: PLS loadings for 1st component





•THROUGHPUT
•NO. OF LINES
Primary Refiners
•SPECIFIC ENERGY
•CONSISTENCY
•PLATE AGE
•STD. DEV. OF MOTOR LOAD
Secondary Refiners
•SPECIFIC ENERGY
•CONSISTENCY
•PLATE AGE
•STD. DEV. OF MOTOR LOAD
•FREENESS
•FIBER LENGTH
•PERCENT FINES
Reject Refiners
•SPECIFIC ENERGY
•PLATE AGE
•FREENESS
•FIBER LENGTH
•PERCENT FINES
Paper Machines
•TEAR MD
•TEAR CD
•BURST
•TSI MD
•TSI CD
•PERMEABILITY

APPENDIX X:

International Peer-Reviewed Publication – 2007 – Chemical Product and Process Modeling Journal

SPATIAL AND TEMPORAL RESOLUTION IN DATA-DRIVEN PROCESS MODELING OF AN INTEGRATED NEWSPRINT MILL

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SUMMARY

Like many globalized industries, the pulp and paper sector finds itself with an increasingly demanding clientele, who continually expect a better and cheaper product. An important design strategy being employed to address this objective is through an analysis of the vast quantity of process and product data accumulated in plant-wide data historians, in order to improve operations. Mill processes are multivariate, meaning that the interactions between the variables are as important as the variables themselves. Process relationships must therefore be modeled as a group, using an appropriate simulation technique like Multivariate Analysis (MVA), with suitable data pre-processing to account for process upsets and other disturbances. In a previous paper, using an Eastern Canadian newsprint mill as an industrial case study, we showed that it was possible to find statistically significant correlations between wood chip refiner operation, intermediate pulp quality, and final paper quality using data-driven models. This was true even though some important process parameters went unmeasured, process lags changed with time, and the operation of key equipment items changed gradually with use. The present study compares the use of different timescales and combinations of unit operations to determine which ones yield the best MVA simulations. Because plant operating data were used and experimental design was not practical, it is possible that some of the correlations found can be attributable to coincidence. We therefore added and removed variables and time periods to explore the validity of the models. The best MVA models were obtained by using a shorter (1-hour) data timescale, although use of a weighted-average filter helped to bridge the gap between these faster readings and the slower paper quality trends.

INTRODUCTION

Globalization of the pulp and paper industry has resulted in customers expecting a better and more consistent product, at competitive price. As a result of these expectations and continued incremental increases in production, at older and smaller Canadian thermo-mechanical pulp (TMP) mills, the quality control and production throughput objectives are typically much higher than when the plants were initially designed.

Analyzing process and product data accumulated by plant-wide data historians is difficult. The feed material is wood in the form of small chips, whose biological origin guarantees complexity. The main process unit operations involve large amounts of mechanical and thermal energy, and their chemistry and physics are not fully known or described by models based on first principles.

Like many process systems, modern newsprint mills are multivariate, meaning that the interactions between the process variables are as important as the actual variables themselves. Univariate and bivariate statistics are therefore inadequate to describe process interactions. The inferential relationships within the plant must be modeled as a group using an appropriate simulation technique like Multivariate Analysis (MVA).

To meet customer requirements, newsprint must have certain properties such as opacity, brightness, and the correct porosity in order to absorb ink adequately. Most importantly, newsprint must be strong enough to withstand the stresses of the printing presses, where paper can move at speeds exceeding 1000 m per minute over dozens of rollers. Strength variability itself can be a major problem. To avoid paper breaks during printing, it is necessary to limit the variations in strength over the length of the paper roll, and between successive rolls.

Working with data from an Eastern Canadian newsprint mill, we showed in a previous paper that it was possible to link the wood chip refining operation, the intermediate pulp quality, and the final paper quality using data-driven models (Harrison *et al*, 2006b). This was done using a variant of MVA known as "Projection to Latent Surfaces" (PLS), a simulation technique in which an X set of variables is linked to a Y set. Unlike traditional process simulators, there is no flowsheet connectivity of any kind implied by the technique. PLS is entirely data driven, working on inputs and outputs only.

By carefully treating the process data, statistically significant correlations were found even though some important process parameters were unmeasured, the process lags changed with time, and the rotating metal plates in the chip refiners wore out gradually over a period of months. An earlier paper (Harrison *et al*, 2006a) had described various methods for pre-treating the operating data from a TMP mill, to counter problems such as equipment shutdowns and production changes.

Building on these previous studies, the goal of the present article is to compare the use of different timescales and combinations of unit operations, to determine which of these yield the best MVA-based process models. When evaluating the models, we consider not only mathematical metrics such as goodness-of-fit, but also the extent to which the model can be interpreted physically. This is critical, since one of the objectives of the methodology is to troubleshoot the process in order to identify possible upstream causes of fluctuations in final product quality. Finally, to explore the validity of the models, we added and removed certain variables and time periods, focusing on cases where the correlations might be attributable to coincidence.

MODELING CHALLENGES

Some parts of an integrated modern newsprint mill, such as wood chip refining, are well instrumented and have a certain degree of redundancy among the measurements. Readings are collected and stored on a second-by-second basis in the data historian. In contrast, many of the downstream operations are characterized by sparse or infrequent measurements, sometimes with one hour or longer between readings. In certain cases, variables that might be important to the process are not measured at all, due to economic reasons or physical constraints. One of the biggest challenges in modeling newsprint quality is therefore to select which variables to use among those that are actually measured.

The variables and data sampling points used in this study are summarized in Table I and Figure 1 respectively. The X variables are the operating parameters for the refining section, where the individual wood chips are converted into pulp by adding mechanical and thermal energy via large rotating plates within the refiners. The Y variables included certain pulp characteristics related to paper quality, and the quality of the final newsprint itself. Note that 'linting' (in Table 1) is the propensity to give off microscopic particles detrimental to ink and glue retention.

One of the main process-related challenges of modeling the newsprint mill was the frequent starts and stops of key unit operations. Along with other familiar data issues such as process lags, instrument drift, calibration, outliers and noise, this made it necessary to pre-treat the operating data from the TMP newsprint mill before performing Multivariate Analysis. In our case, this data pre-treatment included outlier identification and removal (using another MVA variant called "Principal Component Analysis") and filtering based on an exponentially weighted moving average (EWMA). The latter was applied to the 1-h data only, with an alpha value of 0.8, which corresponds to a time constant of 4 h.

TEMPORAL RESOLUTION: USE OF DIFFERENT TIMESCALES

Past papers on TMP production have used a wide range of timescales, from monthly, weekly and daily averages down to instantaneous readings (Nobleza, 1997; Lupien et al., 2001; Saltin and Strand, 1995; Shaw, 2001; Strand et al., 2001; Browne et al, 2004). None of these papers offers an explanation for the choice of timescale. In a non-TMP application, Bendwell (2002) justified the use of 24-hour averages based on the long retention times in pulp-and-paper wastewater basins, suggesting that the time constant of the system at hand should be considered when choosing a timescale. Rosen et al (2001) recommended a multi-scale approach, to allow trends at different frequencies to be studied together.

Even though the data historian contains values recorded every few seconds, creating MVA models at this small timescale would require an inappropriate interpolation of the pulp and newsprint quality measurements. Since these are taken every 45 minutes or longer, interpolated values would be meaningless. Three timescales were therefore selected for this study. The shortest, a 1-h average, was selected because it is close to the pulp sampling period (60-120 min) and the paper sampling period (45 min). It is also close to the 45-min retention time in the 'latency chests', which are large holding tanks at the end of each refining line, where refined fibers are given the time to disentangle.

Interestingly, the use of power spectra on 1-h averages showed that most of the variability in final paper quality occurs at a time constant of more than 10 hours. This is likely the result of control actions at the paper machine, where the pulp is spread, dried and rolled into continuous paper sheets. Control loops maintain constant paper weight, thickness and moisture content, and reduce short-term variations in paper quality. To represent this longer timescale we chose an 8-h average, corresponding to a single workshift. It also corresponds roughly to the overall once-through retention time of the TMP-newsprint mill, typically 6-7 h from chip feeding to final paper rolling.

The third timescale, a 24-h average, represents one day of production and has been used by other authors (Ortiz-Cordoba et al., 2006; Lupien et al., 2001; Saltin and Strand, 1995). The 8-hour and 24-hour means were calculated from a 1-h database with production stoppages and other process upsets removed, rather than directly from the data historian where such outliers would have skewed the values.

SPATIAL RESOLUTION: COMBINING DIFFERENT UNIT OPERATIONS

For this kind of analysis technique, far more complex than the choice of timescale is the question of which variables to use, and in what linear and non-linear combinations. A modern pulp and paper mill has thousands of data collection points, of which hundreds are relevant to product quality. Some of the phenomena within the unit operations are better represented by non-linear combinations of the measured variables; one example being specific refining energy, which is the applied mechanical energy (kW) divided by the pulp throughput (t/h). Combining several production lines, each of which is operated independently, into a single coherent model must also be addressed.

Having explored these issues in previous work, we concluded that the best approach was to aggregate the four wood chip refining lines into a series of global variables, as shown in Table I, some of which are non-linear combinations of the original measurements such as specific energy and consistency (percent solids in the pulp). In this way it was possible to model not just the pulp quality with statistical significance, but also some of the major paper quality parameters as well.

For the present study, a systematic exploration of the model's spatial resolution was completed to determine how far downstream one can go from the most highly instrumented part of the mill (TMP refining), and still be able to model the product quality (pulp or newsprint) adequately. To answer this question, a series of runs were designed using data from different sections of the mill, different months, different years and different paper machines. These are summarized in Table II. Each PLS model had the same X's shown in Table I, but different Y's depending on the trial: pulp at the outlet of the pulping section (3 variables), pulp at the feed to the papermaking section (3 variables), newsprint strength (5 variables), newsprint porosity (1 variable), or newsprint linting (2 variables). The sampling locations for all of these are indicated by the lower-case Roman numerals on Figure 1 and Table II.

MVA models generate a series of 'principal components' that make it possible to represent the variability of the original dataset, but with fewer dimensions. Each component is a linear combination of the original variables, and typically fewer than half-a-dozen of them can capture most of the variability of the initial dataset. The first component explains the most variability, then the second, then the third, and so forth. Each component is statistically independent of the others, and often corresponds to an underlying attribute or 'latent variable' of the system itself. The concept itself is straightforward and was discovered over a century ago, but it is only with the arrival of modern computers that treating large datasets in this way has become practical for applications such as that described here.

For paper quality, earlier work showed that the first component was almost always related to the difference between the two paper machines A and B. In other words, the two paper machines were behaving independently. Even though they each receive the same pulp feed at the same time, the two machines are of slightly different design and are operated separately. We therefore elected to do separate MVA models for each machine.

RESULTS

The results of the PLS analysis for each run are given in Table II. The four different months under study are shown on the left, along with the three time increments of 1 h, 8 h and 24 h. Each column represents a different set of Y variables. The X set is the same for all models. The first number in the table cells is the goodness-of-fit known as Q^2, which represents the proportion of the Y variance captured by the PLS model; it is similar to R^2 but decreases with overfitting. The second figure is the number of principal components required to achieve that goodness-of-fit. The overall results for the entire set of runs are summarized in Table III.

It is important to highlight that the Q^2 value represents the proportion of the Y variance captured by the model, and not the statistical significance of the model *per se*. The latter is indicated by the 95% confidence limits on the PLS histograms. When using real process data, it is common to have Q^2 values in the range of 40%, i.e., the model explains, with reasonable statistical significance, 40% of the Y variance. The unexplained portion of the variance corresponds to unmeasured (or not measurable) process variables that impacted the quality parameters, or to measurement errors and noise, both of which are prominent in real operating data. Note that the Q^2 value listed in Table II is a combined metric for that group of dependent variables; the results obtained would be different if each Y variable had been modeled separately.

As we would expect, the best models were for the pulp sampled immediately downstream of the refining section, followed closely by the pulp sampled further downstream. The only exception is August 2004, where the downstream pulp shows a slightly higher Q^2. The newsprint quality models were less good, significantly so in some cases. Among the newsprint models, paper strength gave the best results, and had a greater number of components, suggesting a higher degree of model complexity. Porosity and linting also showed fairly good models in many cases, but these results were inconsistent from one month to another.

There appears to be a link between the quality of the pulp models for a given month, and the quality of the corresponding paper models, although this trend is by no means linear. It is well known that certain pulp parameters are determinant for paper quality (Law, 2005; Saltin and Strand, 1995; McDonald et al, 2001). However, given the infrequency of measurements taken by automatic samplers, it is to be expected that direct correlation between the variables will not always be found when using real process data. In fact, in some cases the paper models were actually better than the corresponding pulp models, underlining the limitations of the pulp quality data.

To illustrate the concept of model interpretability, Figure 2 shows the first principal component that was found for paper strength at Machine A for August 2003, using 1-h averages. The histogram gives the PLS weightings, known as 'loadings', for each X and each Y variable. The larger the loading, whether positive or negative, the more the variable contributed to that component. Histogram bars in the same direction indicate positive correlation, while those with opposite signs indicate negative correlation. In this case, higher specific refining energy and refining consistency appear to have a positive impact on overall paper strength. This is what one would expect, since pulp having been more developed in the refiners would tend to have more surface micro-fibers and therefore more bonding strength. Higher refining consistency is indicative of gentler refining intensity, and hence fewer damaged fibers, which is also beneficial to paper strength. However, any such interpretations remain conjecture, since MVA itself does not provide definitive process insights. When the results make sense physically, it greatly strengthens the argument that the model is reflective of process fundamentals and not just mathematical happenstance.

In general, the 1-h data models were the best (highest Q^2) and most detailed (highest number of components), followed by the 8-h models and then the 24-h models. The 8-h models had a similar overall structure to those for 1-h. However, there tended to be fewer components, indicating a less complex model. The dominant X's (those with the highest PLS weightings) tended to be very similar to the 1-h case, such that little or no new information about the process could be gleaned at the 8-h timescale.

For the 24-hour averages, the goodness-of-fit, number of components and dominant X's tended to be quite similar to the 8-h case. However, as shown in Figure 3, the uncertainty bars are larger, sometimes many times the size of the PLS loading itself, no doubt because so few points were used to create the model. We could have added more points by modeling, say, a three-month period instead, but that would have destroyed the relative comparison with the shorter timescales.

For some of the 8-h and 24-h models, zero components were found, i.e., no statistically significant PLS model could be generated. This is despite the fact that significant models had been generated using the 1-h data. In such cases, it seems that the use of the longer timescale destroyed the useful information within the dataset, perhaps by filtering out interesting trends. For instance, despite the fairly good 1-h model for March 2003 Machine B paper strength (Q^2 of 44% with 4 components), the corresponding 8-h model had fewer components, a lower Q^2 and much larger 95% confidence bars. The 24-h model had no components at all. Clearly, in this case the daily averages did not contain the process variability that was present in the hourly averages.

In two cases, the Q^2 for porosity was highest at 8-h (Machine A, March 2003 and Machine B, August 2004). In two other cases, the opposite was found, namely the 8-h model was the *poorest* compared to the 1-h and 24-h models. When plotted against time, porosity shows a great deal of variability, much more so than for strength or linting. It would appear that this parameter's idiosyncratic behavior from one month to the next determines which time increment will yield the best model. The underlying cause of these erratic readings could be related to the process itself or to the measurement technique.

EVALUATING LIMITATIONS OF DATA-DRIVEN MODELS

It is critical to understand the limitations of any technique before drawing conclusions from the results. Like any purely statistical technique, MVA is only as good as the data itself. Because we used plant operating data with its inherent characteristics, e.g. natural and sometimes limited variability, influenced by feedback control loops etc., it is possible that some of the correlations were attributable to coincidence.

Determining whether the correlations are attributable to coincidence is by no means obvious. Without a Design of Experiment, there is no way to be certain whether the changes seen in two or more variables are fundamental or just happenstance. However, we can at least double-check whether our models stand up to scrutiny. To this end, we studied the evolution of the process over time within the model space, to see how it behaved, and if any discrete events tended to dominate. We added and removed variables from the models, to make sure that the components we found were not just associated with a single (possibly coincidental) relationship. We also used a time-series techniques known as cross-correlation to investigate the nature of the correlations in the models, as described in Nobleza et al (1990).

The first example, identified by the double lines in Table II, is "Paper Strength, Machine A, 1-h, August 2003". This was a good model, with a Q^2 of 47% and 3 principal components. The PLS loadings were physically plausible, as was shown in Figure 2.

The corresponding score plot is shown in Figure 4. This plot shows how each one-hour observation fits into the overall model, with component 1 as the abscissa, and component 2 as the ordinate. Each one-hour observation has been connected to the previous one by a line, to show the overall time trend throughout the month of August 2003. Note the prominent migration of the data cluster at 519 hours, which corresponds to 3 p.m. on August 21, the moment when the old secondary refiner plates were replaced with new ones.

The critical process-related question is whether the correlations found were real, or simply due to coincidence. It is possible, for example, that the paper strength changed at or around the time that the plates were changed, for a totally unrelated reason. For example, the type of wood chips provided by the supplier might have changed at some point during the month, or a piece of equipment might have undergone maintenance. If so, the PLS algorithm would blindly attribute the change in paper strength to the plate change, if they both occurred around the same time.

The first test made to explore this question was to remove the plate age from the model. This caused the overall Q^2 to drop, which is typical when a well correlated variable is removed. However, otherwise the overall structure of the components remained very similar, suggesting that the correlations found with the other X parameters, such as specific energy, were indeed genuine (Table IV).

We also added two key variables from the paper machine itself, namely paper machine speed and the internal pulp recirculation rate, both of which could be expected to impact paper properties. However, these two new variables were found to contribute very little to the model. If would therefore appear that it is indeed the refiner variables that are linked to the changes in paper strength.

The cross-correlation curve was plotted for two parameters that were prominent in the original loadings plot, namely "2° Specific Refining Energy" and "Tensile Stiffness Index - Machine Direction". The original unfiltered data were used, i.e., without EWMA filtering. As shown in Figure 5, this yielded a correlation coefficient in the range of 0.5-0.6, confirming a significant link between these two variables. The fact that this correlation is evident over a wide range of process lags is indicative of the slowness of the paper quality trends.

Finally, the model was separated into two periods, as shown in Figure 6-a before 2° plate change, and Figure 6-b after 2° plate change. In both cases, the models were poorer. This would suggest that the plate change, and attendant changes in the other process parameters, were relevant to the paper strength. Without the benefit of a designed experiment or bump tests, however, this reasoning remains inductive only.

The second example from Table II is "Paper Strength, Machine B, 1-h, August 2004". The original model had a Q^2 of 37% with 4 components. However, it can be seen that there is a calibration problem with Tensile Stiffness Index (TSI) during that month, as shown in Figure 7. Only the 'Machine Direction' values were affected (i.e., measured in the longitudinal axis of the paper sheet), whereas the paper machine 'Cross Direction' (perpendicular) measurements seem unaffected.

The first component shown in Figure 8 makes it clear that coincidence is at play. Plate age dominates, but all the other variables that are known to be critically important to the process (such as specific energy) are greatly under-represented. This would suggest that the routine changing of the plates that occurred during the month have been spuriously correlated to Tensile Stiffness Index. To remedy this problem, we redid the model using only the data points before the calibration shift. The results are shown in Figure 9. This not only improved the Q^2, but also resulted in a much more logical first component, in which the specific energies and consistencies are prominently correlated with overall paper strength.

CONCLUSIONS

With careful data selection and pre-treatment, it was possible to create strong inferential models for pulp and paper properties using process operating variables. The structure of the models was coherent, and logically interpretable. As expected, the best models were for the pulp immediately downstream of the refining section, followed by the pulp further downstream. The newsprint quality models were somewhat poorer, very much so in some cases.

There appears to be a link between the quality of the pulp models, and the quality of the corresponding paper models, although this was not consistent. Pulp quality is expected to be related to paper quality, but the statistical results do not always bear this out. This highlights the importance of using a multivariate technique; trying to correlate, say, a single pulp property with a single paper property for a single month using bivariate statistics could be very misleading.

The 1-h models were generally the best, followed by the 8-h models, and then the 24-h models. The 8-h models had a similar overall structure to those for 1 h, but tended to have fewer components indicating a less detailed model. For the 24-h models, the uncertainty bars were large, sometimes many times the size of the PLS loading itself, no doubt due at least in part to the smaller number of observations. In some cases zero components were found using 24-h data, meaning that the daily averages simply did not contain the process variability found in the 1-h averages. To achieve the best possible model, it is therefore important to capture some of the faster trends in the refining section by using a shorter timescale, although use of a weighted-average filter helped to bridge the gap between these faster readings and the slower paper quality trends.

For some cases, the PLS model for porosity was best at 8-h, but in other cases the 8-h model was the poorest. This seems to be caused by this parameter's idiosyncratic behavior from one month to the next. This result would tend to justify the multi-timescale approach.

As a general rule, different months yield models with different coefficients, even though the model structure (choice of variables, timescale, etc) remains the same. In other words, the coefficients evolve with time. An automation system based on the MVA models would therefore require an adaptive controller of some kind.

Two examples of possibly coincidental results were considered. The first, involving a plate change, appeared to be a genuine correlation with paper quality based on a comparison of differently structured PLS models drawn from the same database. The second, involving an abrupt shift in tensile stiffness, was almost certainly due to coincidence. These examples highlight the importance of carefully studying all MVA results with an understanding of the underlying processes, to avoid the pitfall of haphazard correlations. Interpreting these black-box models requires a profound knowledge of the process in question.

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Table I. Variables used to generate PLS models of newsprint mill.

Variable	Unit	Time between measurements
X-Variables – Wood chip Refining		
Production rate (proportional to feed screw rotational speed)	t/d	1 second
Number of TMP lines in operation	–	1 second
1° & 2° specific refining energy	kWh/t	1 second
1° & 2° blowline consistency (calculated with simple mass/energy balance)	% solids	1 second
1° & 2° plate age	h	1 second
Standard deviation of motor loads (1° & 2°)	MW	1 second
Reject refining specific energy	kWh/t	1 second
Reject plate age	h	1 second
Y-Variables – Pulp Properties		
Canadian Standard Freeness	mL	60-120 min
Average fiber length (length-weighted)	mm	60-120 min
Fines content, defined as small enough to pass through 200 mesh screen (76 μm)	% (mass)	60-120 min
Y-Variables – Paper Properties		
Strength – Tear strength, Machine Direction (indexed)	$mN/(g/m^2)$	45 min
Strength – Tear strength, Cross Direction (indexed)	$mN/(g/m^2)$	45 min
Strength – Bursting strength (indexed)	$kPa/(g/m^2)$	45 min
Strength – Tensile Stiffness Index, Machine Direction	kNm/g	45 min
Strength – Tensile Stiffness Index, Cross Direction	kNm/g	45 min
Porosity (permeability to air)	mL/min	45 min
Linting (black adhesive patch examined for fine surface particles) – Top	%	45 min
Linting – Bottom	%	45 min

Table II. Grid of PLS models, showing results for each. The first number in each box is the Q^2 obtained for the overall model, i.e., for all the Y variables taken together. Values above 40% are in bold. The second value is the corresponding number of principal components used. The lower-case Roman numerals in the titles indicate the sampling locations on Figure 1.

		X	Y: Pulp		Y: Paper - Machine A			Y: Paper - Machine B		
		Pulping section operating variables	Outlet of pulping section (i)	Feed to paper section (ii)	Strength (iii)	Porosity (iii)	Linting (iii)	Strength (iv)	Porosity (iv)	Linting (iv)
	1 h	✓	38% 4 comp	36% 4 comp	27% 4 comp	30% 2 comp	§	**44%** 4 comp	**47%** 3 comp	§
March 2003	8 h	✓	38% 3 comp	19% 2 comp	*0%* *0 comp*	**58%** 1 comp	§	27% 3 comp	**53%** 2 comp	§
	24 h	✓	17% 3 comp	21% 2 comp	*0%* *0 comp*	**43%** 1 comp	§	*0%* *0 comp*	38% 1 comp	§
	1 h	✓	38% 5 comp	33% 4 comp	**47%** 3 comp	**69%** 3 comp	§	20% 2 comp	26% 2 comp	§
August 2003	8 h	✓	18% 3 comp	17% 2 comp	26% 2 comp	**50%** 1 comp	§	11% 2 comp	37% 2 comp	§
	24 h	✓	10% 1 comp	13% 2 comp	30% 1 comp	**57%** 1 comp	§	6% 1 comp	30% 2 comp	§
	1 h	✓	**44%** 5 comp	**42%** 5 comp	32% 3 comp	**46%** 4 comp	§	26% 3 comp	17% 2 comp	§
March 2004	8 h	✓	34% 2 comp	16% 1 comp	20% 2 comp	8% 1 comp	§	12% 1 comp	21% 1 comp	§
	24 h	✓	26% 2 comp	*0%* *0 comp*	*0%* *0 comp*	*0%* *0 comp*	§	12% 1 comp	*0%* *0 comp*	§
	1 h	✓	**64%** 5 comp	**68%** 5 comp	**53%** 5 comp	**63%** 2 comp	**52%** 2 comp	**37%** 4 comp	**60%** 2 comp	38% 4 comp
August 2004	8 h	✓	37% 1 comp	**44%** 3 comp	*0%* *0 comp*	**51%** 1 comp	35% 1 comp	*0%* *0 comp*	**70%** 2 comp	15% 1 comp
	24 h	✓	**48%** 3 comp	*0%* *0 comp*	13% 1 comp	**52%** 2 comp	28% 1 comp	*0%* *0 comp*	**56%** 2 comp	9% 1 comp

§ No data available for that month.

Table III. Summary of one-hour PLS models obtained for entire grid, showing range of results.

Type of PLS Model (Y variables)	Sampling Location on Figure 1	Number of useful principal components	Range of Q^2	Dominant upstream parameters (X variables)
Pulp Quality – Outlet of pulping section	i	4 to 5	38% to 64%	Plate age, specific energy, consistency, motor load variability (Reject Specific Energy quite prominent)
Pulp Quality – Feed to papermaking section	ii	4 to 5	33% to 68%	Plate age, specific energy, consistency, motor load variability (Reject Specific Energy quite prominent)
Paper Strength (both machines)	iii & iv	3 to 5	20% to 54%	Specific energy, plate age, # of lines, consistency, motor load variability
Porosity	iii & iv	2 to 4	17% to 63%	Plate age, specific energy, # of lines, instability, motor load variability
Linting (August 2004 only)	iii & iv	2 to 4	38% to 52%	Specific energy, consistency, plate age

Table IV. Adding and removing variables from Paper Strength model, Machine A, 1-h, August 2003.

PLS Model	Variables added or removed	Goodness of fit (Q^2)	Number of principal components	Dominant upstream parameters (X variables)
Original model	n/a	47%	3	Specific energy, plate age, # of lines, consistency, motor load variability
Without plate age	All plate ages removed	39%	3	Specific energy, # of lines, consistency, motor load variability
With paper machine parameters	Paper machine speed & pulp recirculation rate added	46%	3	Specific energy, plate age, # of lines, consistency, motor load variability

Figure 1: Data sampling points. There are four parallel pulp lines, each with a primary and a secondary chip refiner. These four lines are combined to feed the pulp preparation section, which subsequently feeds two paper machines operating in parallel. The reject refiners provide a third stage of pulp development to 30-40% of the pulp, key to final paper strength.

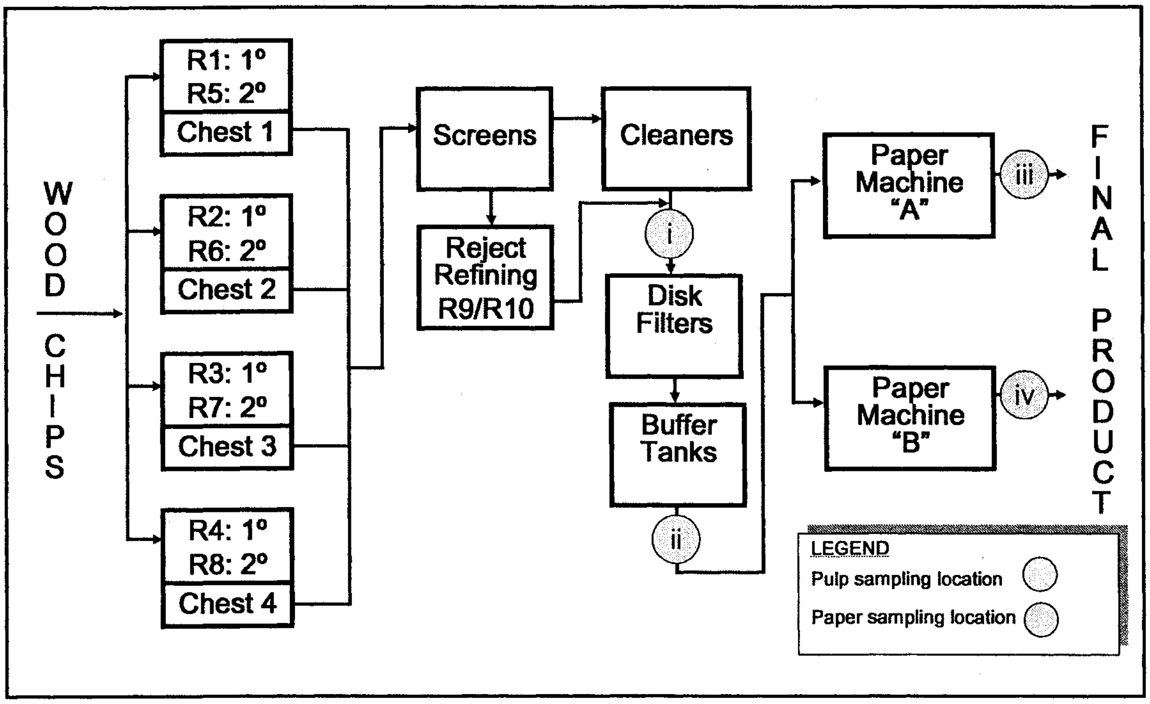


Figure 2: Component 1 loadings for Paper Strength, Machine A, 1-h, August 2003. The Q^2 values indicate the incremental percentage of Y variability captured by that component. The main relationships captured by this component correspond to know process fundamentals, with higher specific refining energy (more fiber development) and higher refining consistency (gentler refining intensity) correlating with stronger paper (better fiber-to-fiber bonding). 182

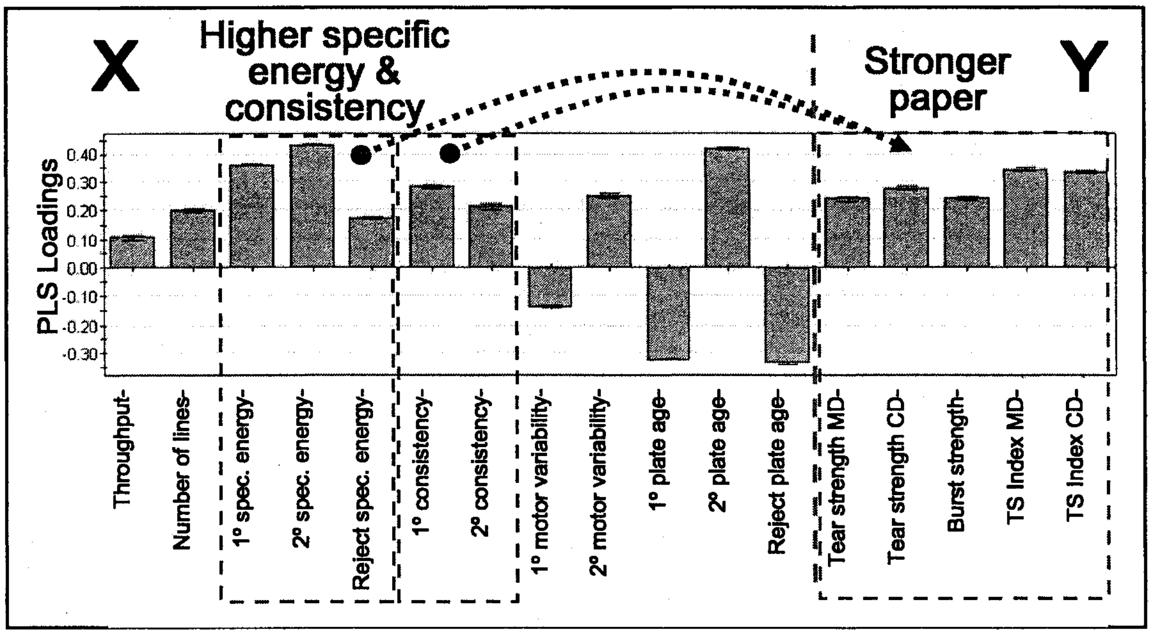


Figure 3: Component 1 loadings for Paper Porosity, Machine A, 24-h, March 2003. Note the large size of the uncertainty bars relative to the actual loadings, despite the high Q^2 (43%) for this component.

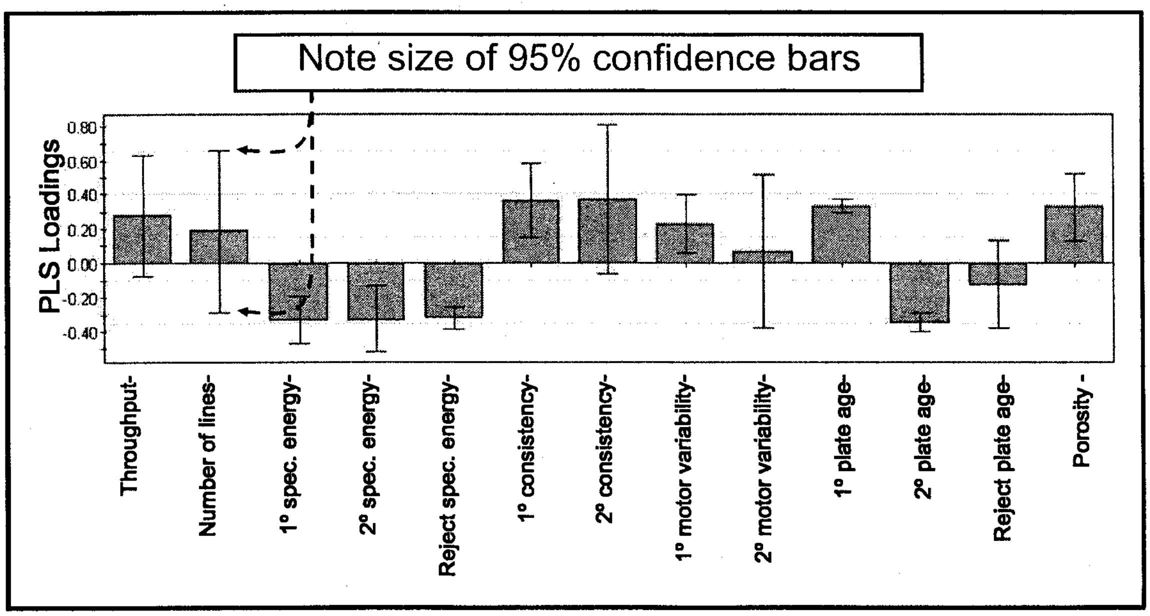


Figure 4: Component 1 & 2 score plot for Paper Strength, Machine A, 1-h, August 2003.
Note 2° plate change.

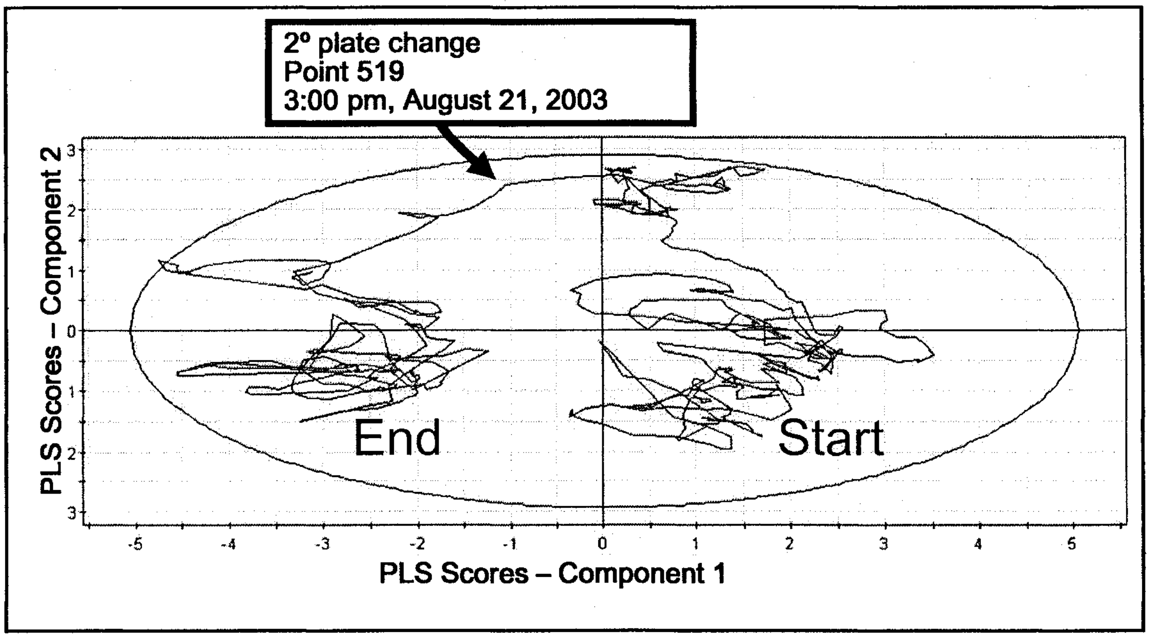


Figure 5: Cross-correlation curve for 2° Specific Refining Energy vs. Tensile Stiffness Index - Machine Direction. Machine A, 1-h, August 2003. Original data used without EWMA filtering.

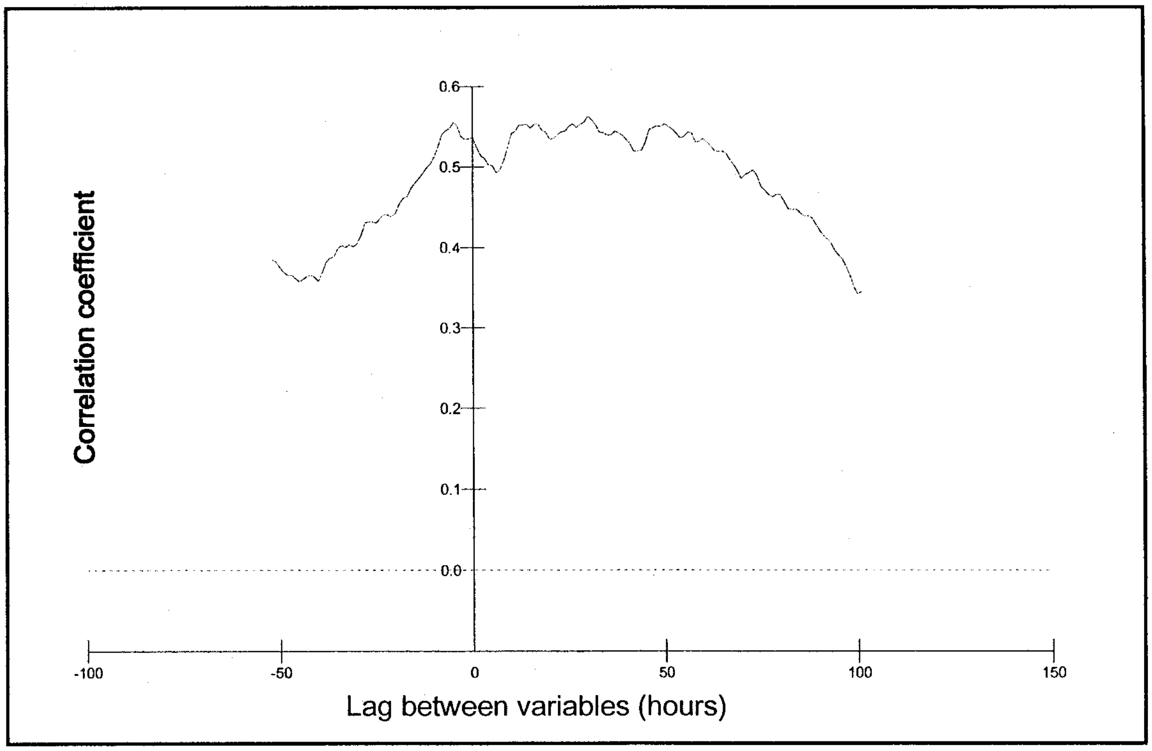


Figure 6: Component 1 loadings for Paper Strength, Machine A, 1-h, August 2003. Split into two periods: a) before 2° plate change, and b) after 2° plate change

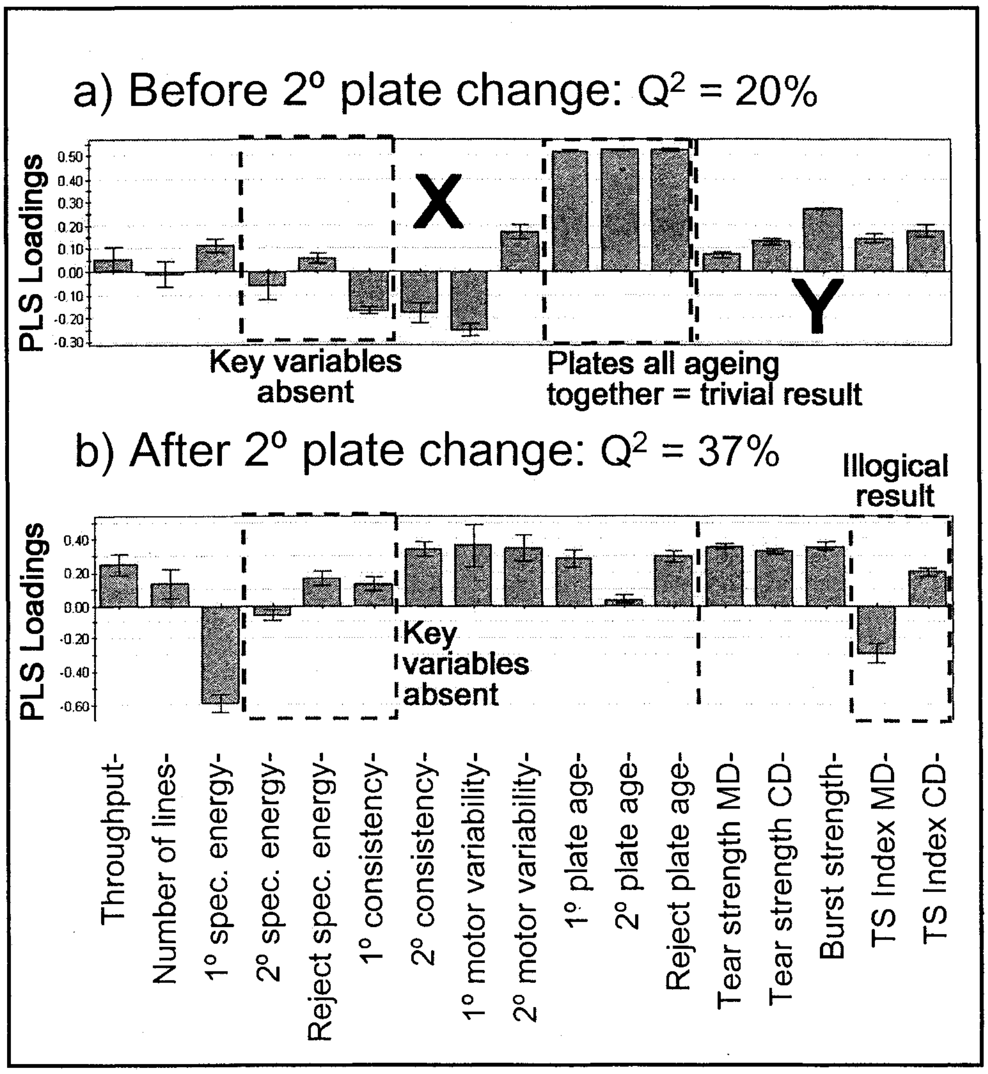


Figure 7: Calibration problem with TSI, Machine B, 1-h, August 2004.

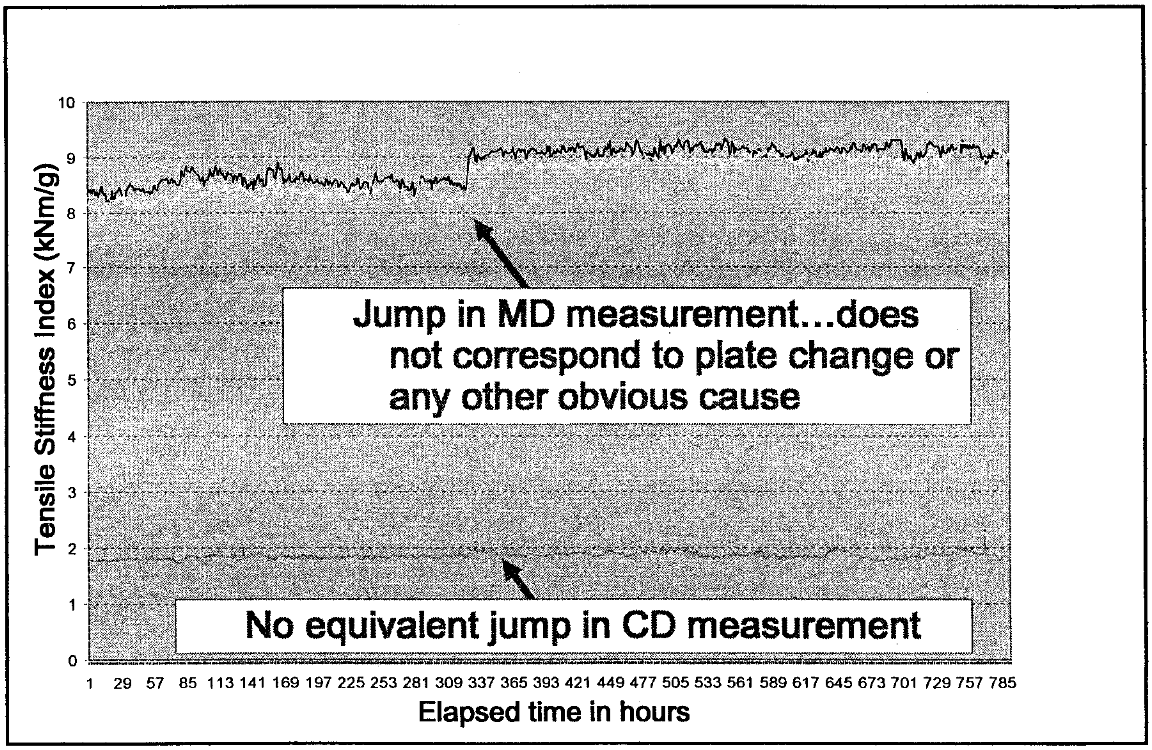


Figure 8: Component 1 loadings for Paper Strength, Machine B, 1-h, August 2004. Using corrupted TSI values.

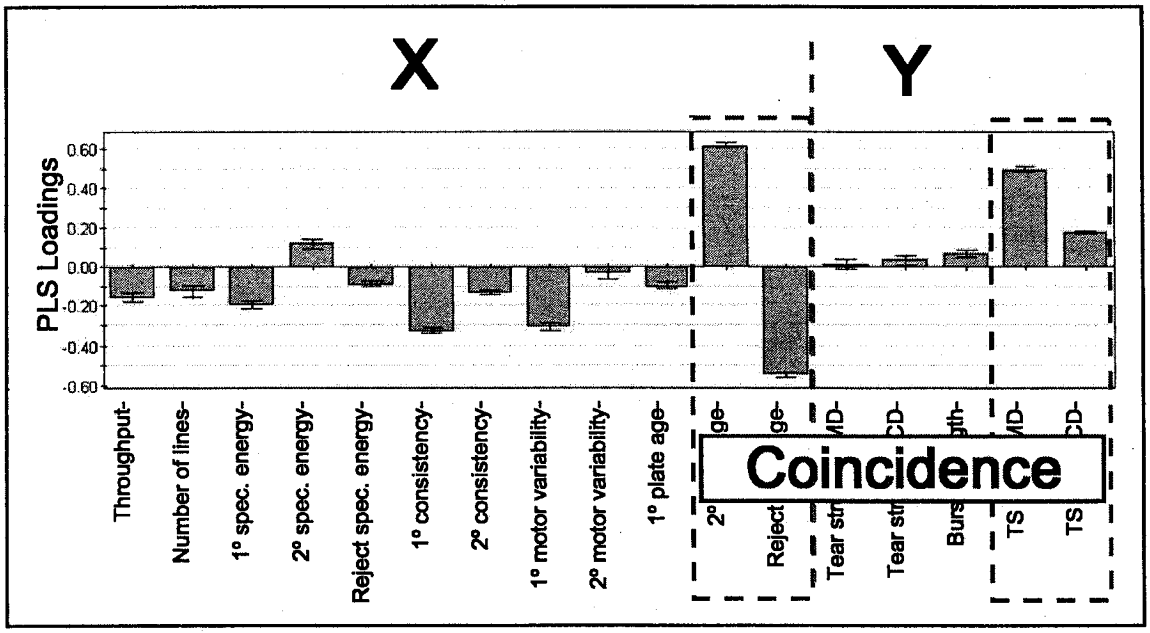
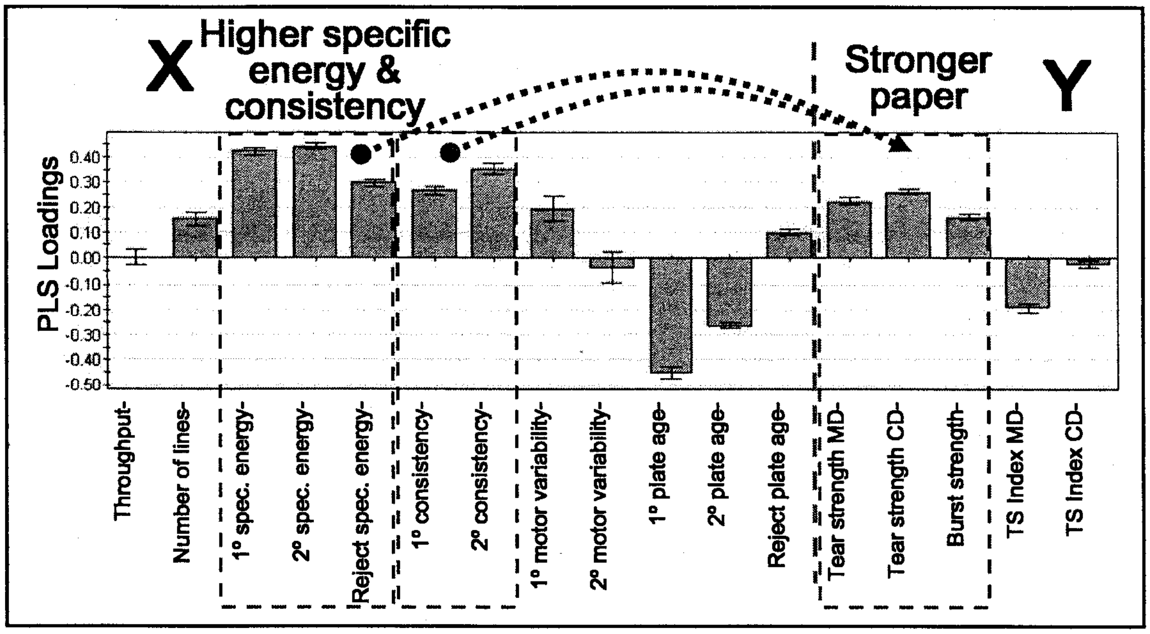


Figure 9: Component 1 loadings for Paper Strength, Machine B, 1-h, August 2004 Using correct values. Q^2 = 53% / 5 components.



APPENDIX XI:

International Peer-Reviewed Publication – 2007 – Industrial & Engineering Chemistry Research Journal (in review)

EXTRACTING PROCESS RELATIONSHIPS FROM HISTORICAL DATABASES OF CONTINUOUS INDUSTRIAL PROCESSES

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SUMMARY

Multivariate Analysis (MVA) is a powerful and proven modeling tool that has been used for studying production data in various industrial sectors. However, production data are rife with outliers, instrument drift, starts and stops of key unit operations, and often product quality sampling is relatively infrequent. Another challenge is combining information from multiple upstream production lines into a single, coherent model of the overall process. This paper outlines a systematic methodology for applying MVA to production data which addresses these challenges. The case study is a thermo-mechanical newsprint mill, a process with a poorly characterized raw material, multiple processing lines experiencing frequent interruptions, and infrequent grab sampling of intermediate and final products. In summary, the methodology involves defining the modeling objective, examining product data, building a suitable model structure using process fundamentals, pre-treating the data, creating models with MVA, interpreting the statistical results, and finally identifying the limitations of the models. Using this methodology led to better MVA models, with respect to both statistical significance and physical interpretability.

1. Introduction and Problem Statement

Multivariate Analysis (MVA) is a powerful and proven tool for troubleshooting, monitoring, and controlling processes in numerous industries, including pulp and paper.[1-7] While the usefulness of MVA is well established, few of the publications in this area have given details on the selection and pre-treatment of process data beforehand. Real production data are rife with outliers, instrument drift, starts and stops of key unit operations, and other factors that that can lead to models that are poor and difficult to interpret. Infrequent sampling of the intermediate and final products is another challenge. Also, in cases with multiple upstream production lines, it is not at all evident how to combine information from each line into a single, coherent model of the overall process.

This paper outlines an explicit methodology for applying MVA to production data from a continuous industrial process. It is based on previous work in data pretreatment[8], process fundamentals related to papermaking[9], and temporal and spatial resolution of MVA models.[10]

The sections that follow provide a background on the challenges encountered when using MVA, an outline of the proposed methodology for addressing these challenges, and finally a case study.

2. Challenges When Using MVA Technique

MVA is a purely statistical black-box technique that generates a small number of new variables known as 'principal components' that capture much of the variability present in the original dataset. In chemical engineering applications, these principal components can often be associated with the fundamental chemistry and physics of the system at hand.

MVA falls into two main categories, Principal Component Analysis (PCA) and Projection to Latent Surfaces (PLS). They differ in that PCA treats all variables as equivalent, whereas PLS distinguishes between X and Y variables. PLS is generally used when there is an expected dependent/independent relationship among the variables. In mathematical terms, PLS is described as follows[28]:

$X = TP^T + E$ outer relation for X
$Y = UQ^T + F$ outer relation for Y
$u_h = b_h t_h$ inner relation for components

Where,

X is an $(n \times k)$ matrix of values for the independent variables;
T $(n \times m)$ is the scores of each X observation on the new components;
P $(m \times k)$ is the loadings of the original X variables on the new components;
E $(n \times k)$ is the residual matrix for X, containing the noise.
Y is an $(n \times l)$ matrix of values for the dependent variables;
U $(n \times q)$ is the scores of each X observation on the new components;
Q $(q \times l)$ is the loadings of the original X variables on the new components;
F $(n \times l)$ is the residual matrix for X, containing the noise;
b_h is the regression coefficient.

The term b_h is the regression coefficient for component number h. A plot of t_h versus u_h for each component gives a visual representation of the correlation structure between the X-space and the Y-space. Thus in PLS, not only must there be correlations within each of the X and Y spaces but, crucially, there must also be a relationship between each pair of X and Y components, otherwise no model is found.

The 'loadings' are the weights assigned to each original variable by the model. The larger the loading, whether positive or negative, the more closely the variable is related to that principal component. The classical approach to computing components is based on eigenvector and eigenvalue theory. In PCA, the eigenvectors of the original X correlation/cross-correlation matrix give the coefficients of the principal components, while the eigenvalues give the variance associated with each principal component. Using this classical approach, all possible principal components are computed at the same time. This can be computationally intensive, especially since only the first few components are typically required to model the system; higher components often represent just noise or other uninteresting results. Modern software packages therefore calculate the components numerically.

For this project we used Simca-P from the Swedish company Umetrics AB, one of the world's most widely used MVA packages for treating process data. We were addressing a design problem, not doing research on the MVA technique itself, and so felt that using a commercially available software was appropriate. However, even when using a commercial package the user is confronted with a series of challenges inherent to any statistical technique, and must make decisions from the start that may affect the final results. These challenges fall into three categories:

- those requiring process knowledge or chemical engineering insight in order to be addressed;
- those requiring statistical, mathematical, or data-oriented solutions; and
- those that are inherent to the technique, and therefore unavoidable.

The first process-oriented decision is to determine the model structure. The user must select which variables to use among the thousands that are typically available in a modern industrial plant. A statistical analysis is only as good as the original data, and MVA emphasizes those variables that are measured better or more frequently.[2] The danger is that some critical variables could be eclipsed by less important variables for which there are more plentiful data.

The components that make up MVA models are linear combinations of the original variables. Fortunately for a well controlled system, the range of the process is relatively limited and it is possible in many cases to model most phenomena as linear.[11] However, when required, new variables can be created based on one or more of the original variables. This is the case, for instance, where the ratio between two measurements (such as applied energy divided by throughput, giving specific applied energy) is closer to the fundamentals of the system at hand than the two original variables themselves.

Partial Least Squares (PLS) is used to maximize the covariance between a set of X variables, such as upstream operating data, and a set of Y variables, such as product quality. These are mathematical, not physical, distinctions. The PLS user must therefore decide whether a given variable is included in the X set or in the Y set.

MVA is a least-squares technique, and thus sensitive to outliers, whether caused by sensor malfunctions, start-up and shutdown of individual pieces of equipment, time lags, or other problems. Direct use of the raw data typically yields poor MVA results, since the algorithm attributes most of the correlations to the data outliers, and not to more subtle changes in the process during normal operation. MVA is likewise sensitive to instrument drift, since this can appear as a long-term trend to which the algorithm ascribes statistical significance. Because variables are usually normalized before use in the MVA model, with mean of zero and standard deviation equal to one, even the smallest trends can take on major significance.

Another decision the user must make is whether to use means, medians, maxima/minima, discrete values, interpolated values, moving averages, standard deviations, or other forms of the original data. Determining which timescales are appropriate is also of key importance, and unfortunately, this is often based on the availability of data rather than on process considerations. Process lags must be taken into account beforehand, otherwise the MVA algorithm will compare unrelated time periods.

Noisy data present a different problem, because MVA is not a time-series technique *per se*. Each fixed time period is treated as a separate observation or trial, unconnected to the others, and thus the presence of spikes will result in a series of trials which bear little resemblance to one other. Another critical question is how to best represent process variability. Recorded values for the variables change with time, providing some variability information to the model, but again MVA is not a time-series technique so the link between consecutive time periods is lost.

Data management systems often use compression to save data storage space, by logging only those values that differ from previously stored values by specified amounts. It has been shown that data compression can impact mean and standard deviation calculations.[12] Ideally, the data compression specification in the data management system is removed, but when using historical data this is not always possible.

MVA models based on process data depend on the recorded variability pre-existing in the dataset. MVA is blind to variables that do not vary significantly, regardless of their actual physical importance. For instance, if the temperature in a chemical reactor were to be kept perfectly constant by process control, it would not correlate with any other variable and would therefore appear to be of no importance. Designed experiments can be used to counter this problem,[13] but this is often not possible or practical for operating processes.

Care must be used when interpreting MVA results, such as assigning cause-and-effect relationships[14]. This is especially true of variables affected by control loops, where the correlations found are opposite to reality due to the action of the controller. MVA models created under closed-loop conditions cannot predict open-loop behavior, or vice versa.[15]

Many authors have emphasized that MVA models should only be applied within the domain in which they are initially calibrated, i.e., assuming that the process will continue to behave in a similar fashion as the original dataset.[16] Past process data may not be helpful in predicting future behavior, a major pitfall. This is of course true of any black-box model in which no scientific principles are used to guide the algorithm. In cases where the process evolves slowly and gradually, adaptive controllers that update model coefficients over time can be used to counter this limitation. However, sudden jarring changes in operating regime may upset this approach.

Finally, MVA results can be difficult to interpret, since it is often not obvious how to assign meaning to components that the technique derives mathematically. Interpretations of MVA results must be based on an understanding of the process fundamentals, since the outputs from the MVA software are purely statistical.[17]

3. Criteria for Evaluating MVA Models

To evaluate and compare the various models obtained, we selected the metric Q^2, which is a measure of goodness of fit analogous to R^2 but specific to predictive power. It is the percentage of overall measured variance that is attributable to the model's predicted values. It is derived by separating the dataset into several segments, some used to create the components, and others for testing the model. Usually 5-10 iterations are used. Unlike R^2, which always increases when a model is made more complex, Q^2 tends to plateau and then diminish sharply when there is over-fitting. The equation for calculating Q^2 is simply[27]:

$$Q^2 = 1 - PRESS/SSX$$

Where,
PRESS = Predictive Residual Sum of Squares (summed for all iterations)
SSX = Sum of Squares

On the physical/chemical side, the models were evaluated with respect to whether they were logically interpretable, i.e., relationship between the various PLS components and the original variables, coherence of variables that are correlated/anti-correlated, which X's were most prominent for modeling the different Y's, and so forth.

4. Proposed Overall Methodology for Troubleshooting TMP Operations Using MVA

To address the MVA challenges outlined in the previous section, we have developed an overall methodology for performing MVA modeling on systems with multiple processing lines and infrequent product sampling. The major steps are illustrated in Figure 1. Each step is described in the paragraphs that follow. An example illustrating this methodology appears in the section that follows.

Step #1 is to define the objective of the modeling activity, and clearly state the objective of the model in the context of the process, e.g., estimating the product compositions from temperature measurements in a distillation column,[18] or controlling a wastewater treatment plant.[19] The modeler should use process and other knowledge to determine whether data is available for the set of X variables likely to affect the set of Y variables.

Step #2 is to study the dataset for final product quality, before doing any kind of statistical analysis. Some data sources are 'rich', with frequent, plentiful data that represent well the underlying process, while other data sources are 'poor', with infrequent grab sampling limited to a handful of parameters. The richness of the product quality data must adequately reflect the trends of interest. The most basic question is whether the right parameters are being measured. The type of equipment used to obtain each measurement must be understood, along with its maintenance and calibration schedules. Plotting each parameter over time can serve to highlight outliers, noise, missing data, overly compressed data, and other problems. Power spectrum and other time-series techniques can be used to ensure that measurement frequency sufficiently represents the variability of each key parameter.

Step #12 is the interpretation of the results with respect to process fundamentals. This is without doubt the most challenging part of the methodology, and requires a good deal of process knowledge and insight into the underlying process principles. MVA models are statistical, and if not built and interpreted carefully, can miss important linkages to the underlying physical phenomena which are of value to the modeler.

Step #13 is to identify the root causes of variability in the final product quality. The purpose of this step is to identify the upstream causes of the variability encountered in the intermediate and final products, to the extent that the data will allow.

Step #14, because MVA is a "black-box" technique, it is very important to determine the limitations of the results, notably with respect to the operating regimes under which they were obtained. We may also be able to identify data gaps which, if addressed, could shed more light on the causes of product quality fluctuations. Adding or removing terms, dividing into shorter time periods, and using time-series techniques can help determine whether the findings are representative of the process, or just coincidence between data sets.

5. Application of Methodology to Industrial Case Study

To illustrate the methodology, we selected the example of a PLS model of bursting strength at a Canadian TMP newsprint mill for the month of August 2003. The TMP newsprint schematic is shown in Figure 2. It may be characterized as a two-step process, with a poorly characterized raw material, multiple processing lines experiencing frequent starts and stops, and infrequent grab sampling of the intermediate and final products.

Table 1 lists the variables used to create the MVA models. A key point is that the quality data for the intermediate product (pulp) and the final product (newsprint) are too sparse and limited to allow statistical modeling of paper quality using only pulp quality. However, both are directly related to the pulp refining operations further upstream, for which there is rich, plentiful, frequent data.

Step #3 is to choose a base timescale. Modern data historians update the values every few seconds, but there is no point in using data at this timescale if the product quality parameters of interest are only measured, say, every few hours. The base timescale must be a compromise between these two extremes. As required, the user can also select multiples of the base timescale to represent slower trends in the process, or to correspond to the time constants of certain parts of the plant. The timescale choice must include a linkage with the overall objectives of the MVA model, such as whether the goal is fast control applications (thus seconds or minutes) or more long-term product quality control (hours) depending on the application.

Step #4 is to select key process variables which alone or in a non-linear combination represent best the process fundamentals. The measurements taken directly from the process instruments are not always 'fundamental', and since MVA is a linear mathematical technique it is important to ensure that the variables are selected and combined in such a way that the actual underlying process is being represented as much as possible. This step can require a profound understanding of the process being modeled. Merely choosing a list of convenient measurements and putting them together could result in a weaker MVA model.

Steps #5 through 9 relate to data selection and pre-treatment, based largely on previously published work.[8] These steps include systematically removing dubious periods of operation such as low production and aberrant process behavior, calculating derived variables that are representative of the process fundamentals, synchronizing the data to account process lags, combining upstream production lines, and filtering. These steps are explained in more detail in the case study in the following section.

Steps #10 and 11 are the creation of the MVA models for the intermediate and final product quality (Y variables) based on critical process variables (X variables). We used a commercially available software, but the MVA algorithm is public knowledge so it is also possible to calculate the components from scratch.

Table 1 also gives the sampling frequencies for the different variables. The key operating variables around the refiners are measured every few seconds (the data historian's lowest time increment), whereas pulp quality is measured only every 60-120 minutes. The final paper is sampled on average every 45 minutes. We therefore chose one-hour averages as the logical starting point.

Following the technique recommended by a previous author[20] we studied the power spectra of the paper strength parameters, using one-hour averages. As reported previously,[9] it was found that three-quarters of the variability occurred at a time constant above 10 hours. Over 95% of the variability occurred at a time constant above 2.5 hours, probably due to control loops at the paper machine. This is where the pulp is spread onto the paper machine wire, pressed, dried, and rolled into continuous paper sheets. Control loops on these machines maintain constant paper weight, thickness and moisture content, and reduce short-term variations in paper strength. These results would suggest that the slower trends in final paper quality are indeed adequately represented, and that a sampling frequency of 45 minutes is sufficient for our purposes.

Selecting which upstream variables to use was challenging. It is well known that certain pulp parameters are determinant for paper quality.[17,21,22] Specific refining energy is the central parameter for TMP refining, and it must be high enough to ensure fiber separation and defibrillation, but low enough to avoid excessive fiber cutting which can adversely impact the strength of the final paper.[23]

The concept of 'refining intensity' is much more difficult to measure in an industrial refiner. It indicates how the mechanical energy is applied to the wood fibers, whether gradually over a large number of bar impacts, or suddenly by just one or two jarring impacts. The latter situation is highly damaging to fibers.[24,25] For a given plate configuration and disc rotation speed, refining intensity is largely a function of refining consistency[23] (percent solids in the pulp). This is an inverse relationship: higher consistency means a longer fiber residence time between the refiner plates, and hence more bar impacts of lower refining intensity for a given specific energy.

Plate age is known to be a major factor in refining operations, since the refiner plates wear out gradually, changing the shape and depth of the grooves on their working surfaces, and thus the refining conditions experienced by the wood fibers.[26]

The model structure was therefore selected to address all of these critical process fundamentals, by aggregating the four pulp lines into a series of global variables. Some of these were non-linear combinations of the original measurements.

The main data pretreatment steps are illustrated in Figure 3. The first step is to remove periods of low production and other major outliers, otherwise they disrupt useful information in the dataset. The next step is to calculate the derived variables, based on the process-oriented logic outlined above. Specific refining energy and refiner consistency were not measured directly, and thus had to be calculated from other existing variables based on mass and energy balance information.

Synchronization is necessary because MVA is not a time-series technique, and will only associate data that appear within the same 'observation'. Process lags were determined based on flowsheet knowledge, plus time-series techniques such as cross-correlation curves. At the case study mill, the process lags for the mainline pulp are not constant because of changes in tank levels. However, for the purposes of this study the monthly average lags between unit operations were used.

One of our goals was to avoid having idiosyncrasies in any one pulp refining line dominate the model. Our reasoning was to mimic as closely as possible what the pulp itself actually experiences, which in this case is a mixing of all refining lines before proceeding to the papermaking section. Note that low production periods and other questionable data had been removed before combining the process lines, to ensure that the combined variables would only represent steady state operation.

Finally, filtering was applied to the raw data. Using a one-hour average is already a form of filtering, but in addition, we applied EWMA filtering to all X and Y variables to smooth out spikes. A filtering coefficient (α) of 0.8 was selected, corresponding to a time constant of 4 hours. The goal was match the estimated overall residence time of the plant, which is roughly 4-6 hours from raw material feed to final paper rolling. The EWMA filtering has two advantages: elimination of measurement noise, and approximation of process dynamics

Using stored data for the key variables such as motor load revealed that the time between recorded values was as high as 30 to 40 seconds in some instances, amounting to a loss in resolution in the signal (the exception test limit was ±1% and the compression test limit ±2%). However, for the most part one-hour averages were used, so this was not expected to have an impact on the results. Plotting each variable over time in EXCEL served to ensure that there were no regular staggered patterns indicative of excessive compression.

An example of the MVA modeling results is shown in Figure 4. The model explains roughly half of the variability in the paper strength (47%) using just three components, down from dozens of variables in the original dataset. The unexplained portion of the variability may be due to a variety of factors such as unmeasured factors affecting the process, measurement error, noise, instrument drift, or a combination of these. Models obtained using other time periods and other paper quality parameters gave equally promising results, with Q^2 values ranging from 17% (in one problematic case) to as high as 63%.[10]

The first component in Figure 4 shows a link between specific energy and refiner consistency and paper strength. The second component is dominated by secondary plate age, corresponding to the shift in process characteristics related to a change for newer plates known to have taken place at hour 519 of the month in question. The third component correlates overall throughput with an increase in tear and burst strength, but a decrease in Tensile Stiffness Index (TSI). This component is more difficult to interpret, but in any case it only provides an incremental Q^2 of 3% and so may not be pertinent.

Based on these results, it appears the model is both statistically significant and physically plausible. To verify whether the model obtained using the proposed methodology was indeed better, we compared PLS models for the before and after cases as shown in Table 2. Exactly the same time period and Y variables were used (Paper Strength for

August 2003), but this time the X's were the original variables from the data historian, with no prior data pretreatment. As shown in the table, the goodness-of-fit of the model using our proposed methodology was almost twice that of the untreated case. Furthermore, fewer components were required to capture that amount of process variability, suggesting that the model was closer to the fundamentals of the system at hand.

Figure 5 gives an example of the difficulty of interpreting models using the original variables. Again, the Y variables are the same as in Figure 4, but the X variables are much more numerous. The similarities to Figure 4 are apparent, but in this case Production Line 3 dominates, and Line 4 is almost absent from the model. The higher components were even harder to interpret, and had the added problem of very large 95%-confidence bars, often larger than the histogram bar itself, making their statistical significance highly questionable.

6. Caveats About Applying MVA Models for Process Control

Several authors and companies have proposed control strategies for TMP newsprint mills based on models generated using MVA techniques. An obvious question is whether the results of this kind of MVA analysis can serve to generate a robust Model-Predictive Control (MPC) system.

For the purposes of prediction, it is possible to represent a PLS model in the form of a classic regression equation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots$$

The results for our case study are presented in Table 3. The coefficients for the same month of the subsequent year are also shown, and the percent difference between the coefficients. There is an enormous change in some cases, in the order of several hundred percent. Clearly, then, an adaptive MVA model of some kind would be required to control the process.

Based on our experience, we believe the coefficients would have to be updated in the order of once per day in order to follow the process adequately. Also, it would be preferable to have several sets of equations to cover known process scenarios such as new plates in the refiners, otherwise the controller could be overwhelmed by sudden large shifts.

No bump tests or experimental designs were used to generate our models, which were entirely based on pre-existing production data. It is therefore impossible to know if each variable is correctly represented. For instance, there might be an arbitrary split of coefficient weightings between two variables, which works well for the case at hand but would be totally erroneous under other circumstances. This may explain the large differences in Table 3 coefficients; they contain not only the difference between the different years, but also randomly assigned differences inherent to the method used.

Assuming that this situation could be addressed by performing planned experiments, it would still be necessary to capture the process dynamics adequately. Regardless of the process control application being considered, there would have to be an overall approach that accounts for data lags, data filtering, and time averaging. The goal is to lag and filter the upstream variables in a sort of simulation of the process dynamics, so that they will be synchronized with each other and, more importantly, the final paper properties.

Dynamics can be approximated by pure time delays or time lags and time constants. For our case study, we assumed a overall transport lag from chips to paper of 4-6 hours, and adjusted the filtering coefficient accordingly. This is a highly idealized assumption, given the lack of plug flow, the presence of recycle loops, and fluctuations in storage tank levels. We used averaged values for these lags, taken over a longer period. For this application, it was unnecessary to represent the dynamics more accurately, because the paper quality variations under study were mostly long term. If the modeling objectives had been more short term, it might have been useful to try to link process lags to the storage tank levels.

Other techniques for dealing with process dynamics with MVA could the use of a autoregressive model structure, in which previous Y values are included as X variables. This is good for prediction, but not good for trouble shooting. Another possibility would be to introduce lagged X variables, which adds complications and may make the model difficult to interpret.

In short, when studying industrial production data, dealing with process dynamics must be a major part of any MVA modeling.

7. Discussion

The methodology was applied as a case study to a thermo-mechanical newsprint mill, with a poorly characterized raw material, multiple processing lines experiencing frequent starts and stops, and infrequent product sampling. The main findings were as follows:

- MVA is a least-squares technique, and thus highly sensitive to outliers. We recommend pre-treating the data, including systematically removing dubious periods of operation such as low production and aberrant process behavior, calculating derived variables, synchronizing the data, combining upstream production lines, introducing process lags, and filtering.
- The timescale choice must include a linkage with the overall objectives of the MVA model. It is important to characterize which data sources are 'rich', with frequent, plentiful data, and which are 'poor', with infrequent grab sampling.
- Regardless of the process application being considered, accounting for data lags, data filtering, and time averaging is critical to capturing the necessary dynamics. For example, in the case study the EWMA filtering coefficient was selected to correspond to the estimated overall residence time of the plant.
- Since MVA is a linear mathematical technique, it is important to ensure that the variables are selected and combined in such a way that the process fundamentals are reflected as much as possible. For the case study, emphasis was placed on key process fundamentals such as specific refining energy, refining intensity, refining consistency, and plate age.
- No bump tests or experimental design were used to generate our models, which were entirely based on pre-existing production data. It is therefore impossible to

attribute cause-and-effect relationships, or to know how accurately each individual variable was represented.

With regard to process applications, the proposed methodology could make a better statistical link between the decisions made by operators, and the impacts on final product quality. By making the best possible use of real operating data, the model was able to explain roughly half of the variability in the paper strength using just three components, down from dozens of variables in the original dataset. This would suggest that the newly created PLS components are themselves closely related to the underlying fundamentals of the system.

This project focused on process troubleshooting, but the results could have implications for process monitoring applications. For instance, the first component showed a strong link between specific energy and refiner consistency with respect to paper strength. This is consistent with current knowledge of fiber physics. However, the coefficients change from one month to the next, so the degree to which the paper quality is impacted by these parameters changes with time. By creating a statistical link using real operating data, it should be possible to inform the operators of conditions where the paper is most sensitive to changes in these parameters, notably refining consistency which is difficult to measure and must often be calculated from other variables.

The second component was dominated by secondary plate age. This is not surprising, and corresponds to known process fundamentals. However, the fact that the secondary plate age had more impact than, say, primary or reject plate age could alert the operators to a situation where final paper strength is being affected. Again, the degree to which a known process parameter affects the final paper quality will vary from one month to the next, so having a method for tracking such effects could be very beneficial to the operators.

The statistically demonstrated influence of rejects refining on final paper quality is another area where the project results could help improve the process. Generally, what happens in rejects refining is the result of decisions made in other parts of the plant. The extent to which these decisions are indirectly affecting final paper quality might be more apparent if the ever-changing statistical correlations were better known and available to the operators.

Regarding to applications to process control, it is possible to use this kind of PLS model to predict new process outputs. However, in our case study there was an enormous change in the coefficients from one month to the next, in the order of several hundred percent. Clearly an adaptive controller of some kind would be required to automate the TMP process. It would be preferable to have several sets of equations to cover known process scenarios such as new plates in the refiners, otherwise sudden jarring changes in operating regime could disrupt the controller. Based on our experience, we believe the coefficients would have to be updated in the order of once per day in order to follow the process adequately.

8. Conclusions

This paper outlines an explicit, detailed methodology for applying MVA to production data from continuous industrial processes. In summary, the methodology involves defining the modeling objective, examining product data, building a suitable structure using process fundamentals, pre-treating the data, creating models with MVA, interpreting the statistical results, and finally identifying the limitations of the models. The case study yielded results that were not only statistically significant, but also physically interpretable with regard to process fundamentals. Using this methodology led to better MVA models, with respect to both statistical significance and physical interpretability.

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(5300 words, not including main titles or summary)

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Table 1. Variables used to generate PLS models of newsprint mill.

Variable	Unit	Time between measurements	Mean[§]	Standard deviation[§]
X-Variables – Wood chip Refining				
Production rate (proportional to feed screw rotational speed)	t/d	1 second	990.9	143.0
Number of TMP lines in operation	–	1 second	3.49	0.64
1° specific refining energy	kWh/t	1 second	1069.1	55.8
2° specific refining energy			910.1	59.0
1° blowline consistency (calculated with simple mass/energy balance)	% solids	1 second	51.67	1.79
2° blowline consistency (calculated with simple mass/energy balance)			49.33	3.09
1° plate age (sum of four refiners)	h	1 second	4051.2	798.0
2° plate age (sum of four refiners)			3879.1	996.2
Standard deviation of 1° motor load	MW	1 second	0.195	0.032
Standard deviation of 2° motor loads			0.441	0.096
Reject refining specific energy	kWh/t	1 second	1162.3	130.0
Reject plate age (sum of two refiners)	h	1 second	2117.8	816.1
Y-Variables – Pulp Properties				
Canadian Standard Freeness	mL	60-120 min	187.6	21.1
Average fiber length (length-weighted)	mm	60-120 min	1.23	0.07
Fines content, defined as small enough to pass through 200 mesh screen (76 μm)	% (mass)	60-120 min	5.95	0.84
Y-Variables – Paper Properties				
Strength – Tear strength, Machine Direction (indexed)	$mN/(g/m^2)$	45 min	4.39	0.25
Strength – Tear strength, Cross Direction (indexed)	$mN/(g/m^2)$	45 min	6.36	0.36
Strength – Bursting strength (indexed)	$kPa/(g/m^2)$	45 min	1.53	0.11
Strength – Tensile Stiffness Index, Machine Direction	kNm/g	45 min	8.27	0.39
Strength – Tensile Stiffness Index, Cross Direction	kNm/g	45 min	2.16	0.09
Porosity (permeability to air)	mL/min	45 min	361.6	80.3
Linting (black adhesive patch examined for fine surface particles) – Top	%	45 min	2.81	0.92
Linting – Bottom	%	45 min	2.62	0.88

§ Based on hourly readings for the months of March and April in 2003 and 2004, after removal of major outliers but before application of EWMA filtering.

Table 2. PLS modeling results before and after application of proposed methodology, Paper Strength, August 2003.

Model	Goodness of fit (Q^2)	Number of components required	Interpretability
Original variables used directly in PLS model	25%	5	Very difficult due to idiosyncrasies of component loadings for separate production lines, as shown in Figure 5.
PLS model obtained after applying proposed methodology	47%	3	Clearly interpretable as shown in Figure 4.

Table 3. PLS regression coefficients for Bursting Strength in kPa/(g/m^2), Paper Machine A.

Symbol	X variable	Coefficients for August 2003	Coefficients for August 2004	Percent difference 2004 vs. 2003
β_0	Constant	6.8E-01	1.6E+00	133.8%
β_1	Production rate	8.2E-05	4.6E-05	-44.6%
β_2	Number of TMP lines in operation	2.0E-02	9.4E-03	-54.0%
β_3	1° specific refining energy	1.4E-04	7.6E-05	-46.2%
β_4	2° specific refining energy	2.3E-04	2.3E-04	-1.1%
β_5	Reject refining specific energy	1.4E-04	-7.0E-05	-151.2%
β_6	1° blowline consistency	-2.2E-03	-1.1E-02	384.1%
β_8	2° blowline consistency	-1.5E-03	3.5E-03	-328.3%
β_9	Standard deviation of motor load (1°)	-3.6E-01	2.1E-02	-105.9%
β_{10}	Standard deviation of motor load (2°)	3.9E-01	2.7E-01	-29.9%
β_{11}	1° plate age	-3.3E-06	1.4E-05	-509.9%
β_{12}	2° plate age	7.2E-05	-2.7E-05	-137.4%
β_{13}	Reject plate age	-5.6E-06	-2.0E-05	249.5%

CAPTIONS FOR FIGURES

Figure 1: Proposed overall methodology for MVA modeling with multiple processing lines and infrequent product sampling.

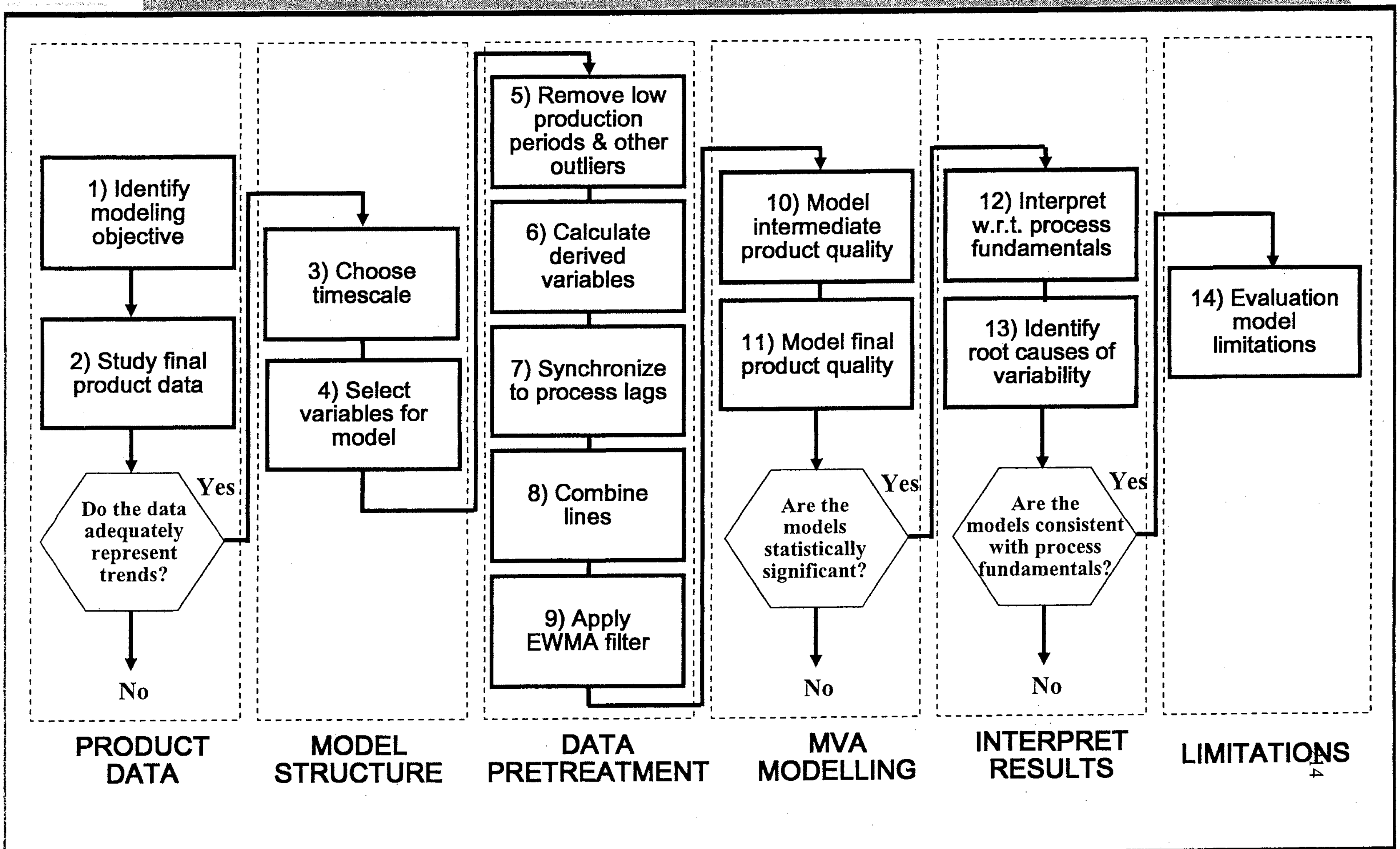
Figure 2: Generic representation of a thermomechanical newsprint mill.

Figure 3: Data pre-treatment approach used for case study.

Figure 4: PLS loadings for Paper Strength, Paper Machine "A", August 2003. Obtained using proposed methodology.

Figure 5: PLS loadings for first principal component, using original variables. Paper Strength, Paper Machine "A", August 2003.

Figure 1



1) Identify modeling objective
2) Study final product data
Do the data adequately represent trends?
Yes
No
3) Choose timescale
4) Select variables for model
5) Remove low production periods & other outliers
6) Calculate derived variables
7) Synchronize to process lags
8) Combine lines
9) Apply EWMA filter
10) Model intermediate product quality
11) Model final product quality
Are the models statistically significant?
Yes
No
12) Interpret w.r.t. process fundamentals
13) Identify root causes of variability
Are the models consistent with process fundamentals?
Yes
No
14) Evaluation model limitations
PRODUCT DATA
MODEL STRUCTURE
DATA PRETREATMENT
MVA MODELLING
INTERPRET RESULTS
LIMITATIONS

Figure 2

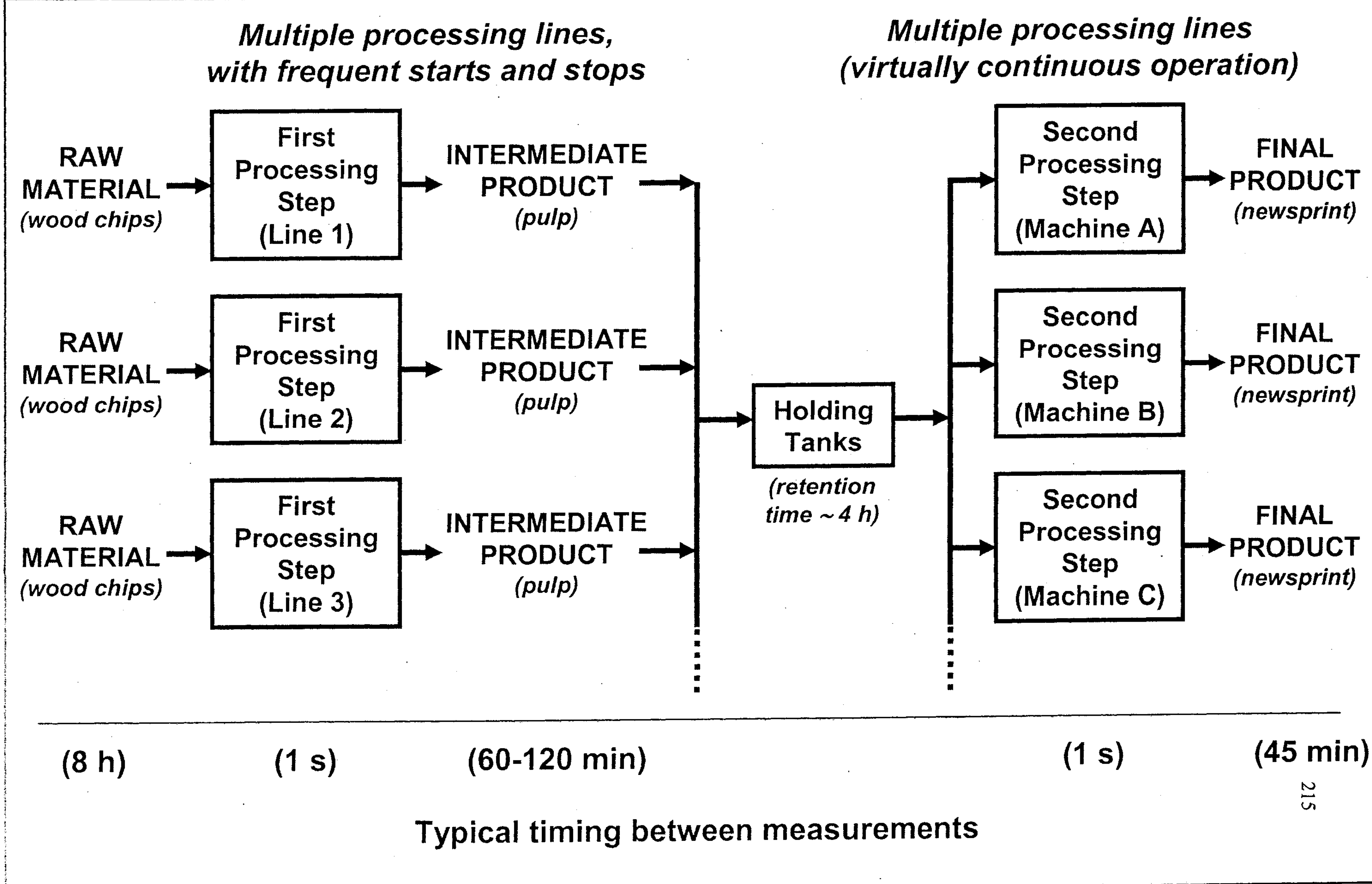
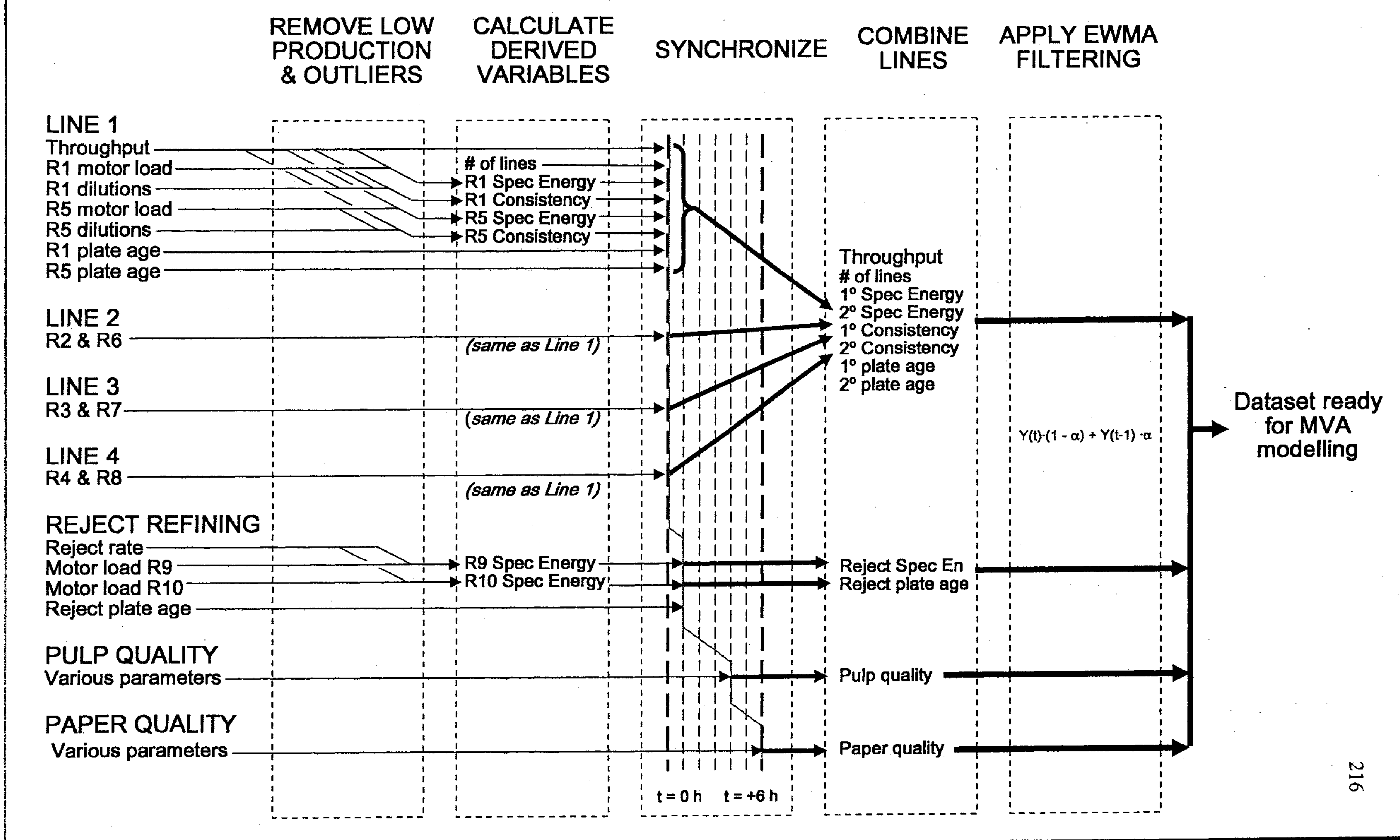
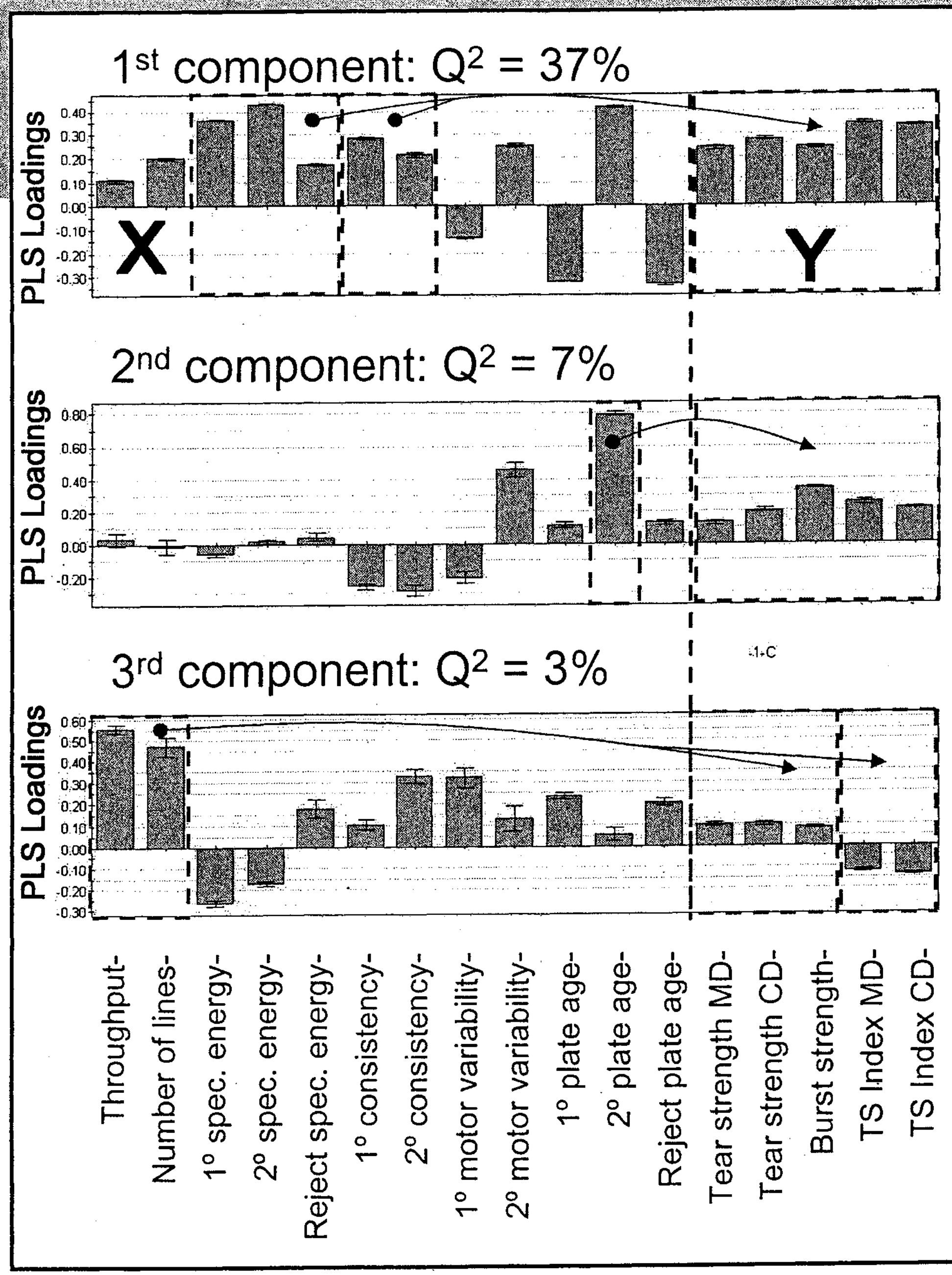

Multiple processing lines,
with frequent starts and stops
Multiple processing lines
(virtually continuous operation)
RAW MATERIAL (wood chips)
First Processing Step (Line 1)
INTERMEDIATE PRODUCT (pulp)
RAW MATERIAL (wood chips)
First Processing Step (Line 2)
INTERMEDIATE PRODUCT (pulp)
RAW MATERIAL (wood chips)
First Processing Step (Line 3)
INTERMEDIATE PRODUCT (pulp)
Holding Tanks
(retention time ~ 4 h)
Second Processing Step (Machine A)
FINAL PRODUCT (newsprint)
Second Processing Step (Machine B)
FINAL PRODUCT (newsprint)
Second Processing Step (Machine C)
FINAL PRODUCT (newsprint)
(8 h)
(1 s)
(60-120 min)
(1 s)
(45 min)
Typical timing between measurements

Figure 3



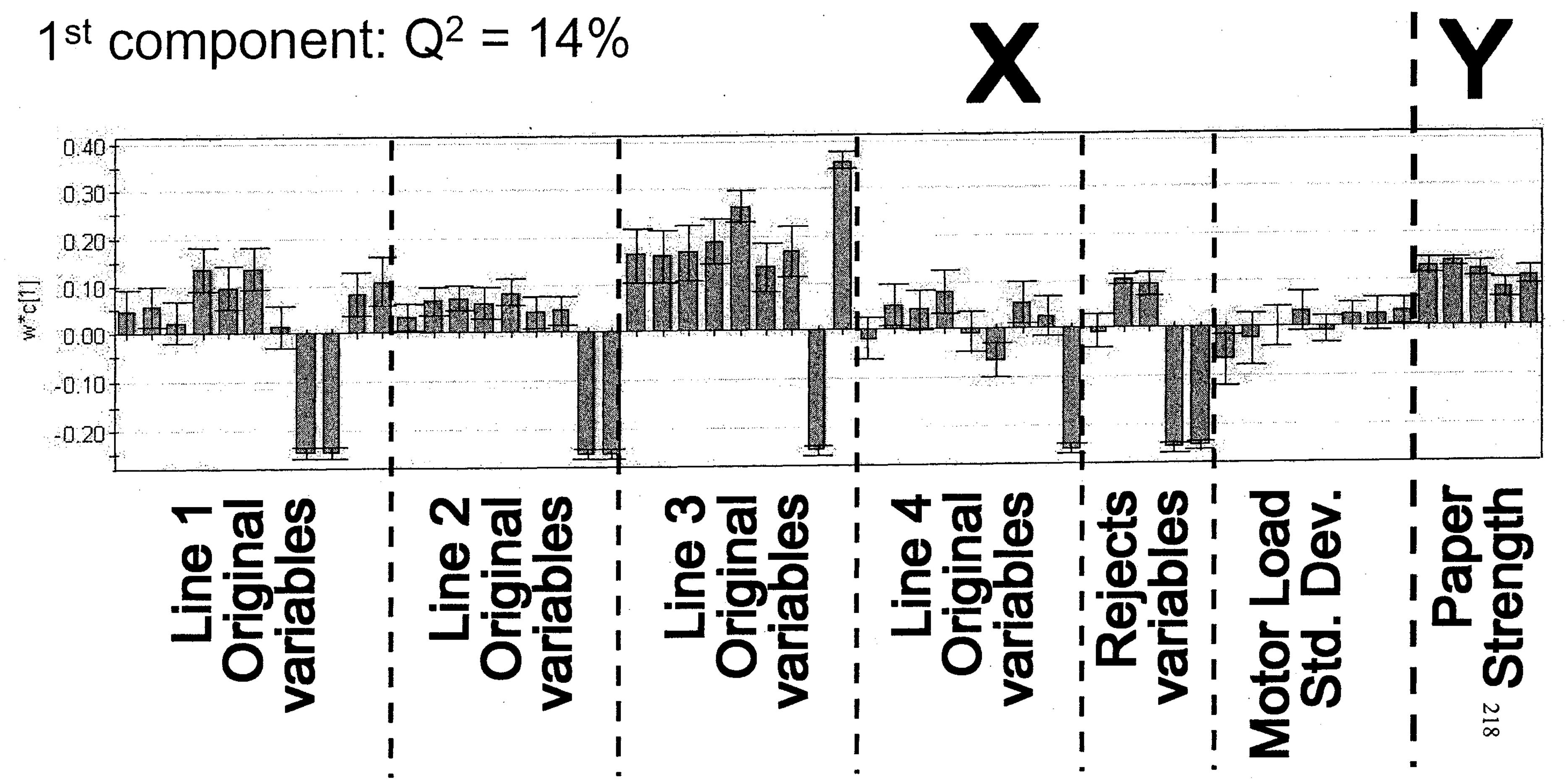
REMOVE LOW PRODUCTION & OUTLIERS
CALCULATE DERIVED VARIABLES
SYNCHRONIZE
COMBINE LINES
APPLY EWMA FILTERING
LINE 1
Throughput
R1 motor load
R1 dilutions
R5 motor load
R5 dilutions
R1 plate age
R5 plate age
# of lines
R1 Spec Energy
R1 Consistency
R5 Spec Energy
R5 Consistency
LINE 2
R2 & R6
(same as Line 1)
LINE 3
R3 & R7
(same as Line 1)
LINE 4
R4 & R8
(same as Line 1)
REJECT REFINING
Reject rate
Motor load R9
Motor load R10
Reject plate age
R9 Spec Energy
R10 Spec Energy
PULP QUALITY
Various parameters
PAPER QUALITY
Various parameters
t = 0 h
t = +6 h
Throughput
# of lines
1° Spec Energy
2° Spec Energy
1° Consistency
2° Consistency
1° plate age
2° plate age
Reject Spec En
Reject plate age
Pulp quality
Paper quality
Y(t)·(1 - α) + Y(t-1) ·α
Dataset ready for MVA modelling

Figure 4



1st component: Q2 = 37%
2nd component: Q2 = 7%
3rd component: Q2 = 3%
PLS Loadings
X
Y
Throughput-
Number of lines-
1° spec. energy-
2° spec. energy-
Reject spec. energy-
1° consistency-
2° consistency-
1° motor variability-
2° motor variability-
1° plate age-
2° plate age-
Reject plate age-
Tear strength MD-
Tear strength CD-
Burst strength-
TS Index MD-
TS Index CD-

Figure 5


1st component: Q2 = 14%
X
Y
0.40
0.30
0.20
0.10
0.00
-0.10
-0.20
w*c[1]
Line 1 Original variables
Line 2 Original variables
Line 3 Original variables
Line 4 Original variables
Rejects variables
Motor Load Std. Dev.
Paper Strength

APPENDIX XII:
Details of Key MVA Modelling Runs

March 2003

- Data pre-treatment
- PCA outliers removed
  - Score Plot
  - Distance-to-model
- EWMA with $\alpha = 0.8$

Definitive runs/1_graphs

ÉCOLE POLYTECHNIQUE MONTRÉAL

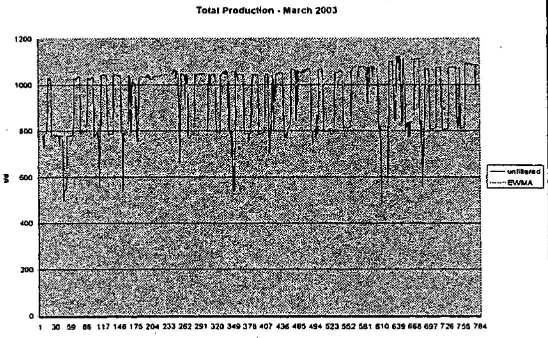
The « Big Grid »:
a.k.a. Overall Experimental Design

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej +	AlimFAD	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

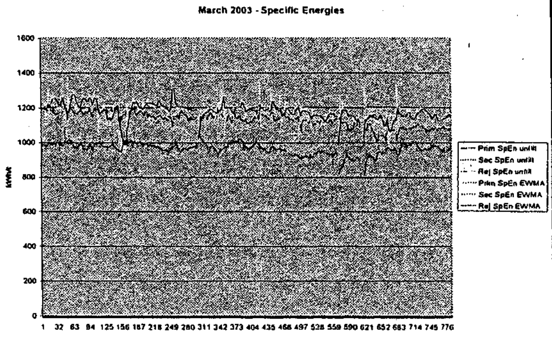
Definitive runs/1_graphs

ÉCOLE POLYTECHNIQUE MONTRÉAL

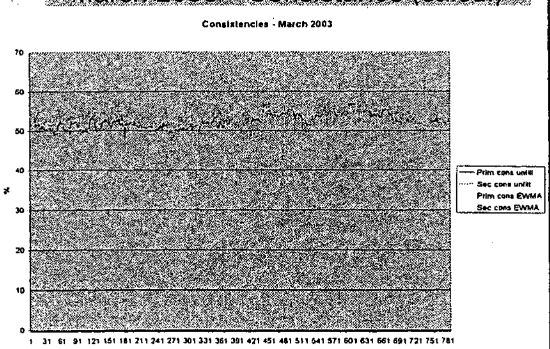
March 2003 – Production 4 lignes



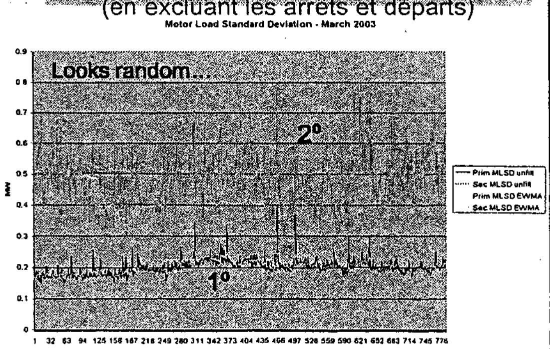
March 2003 – Énergies spécifiques

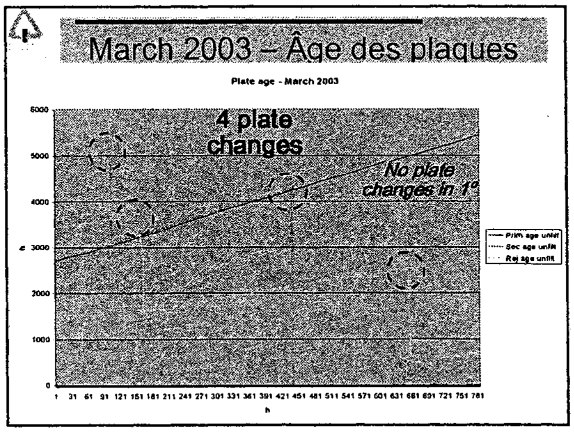


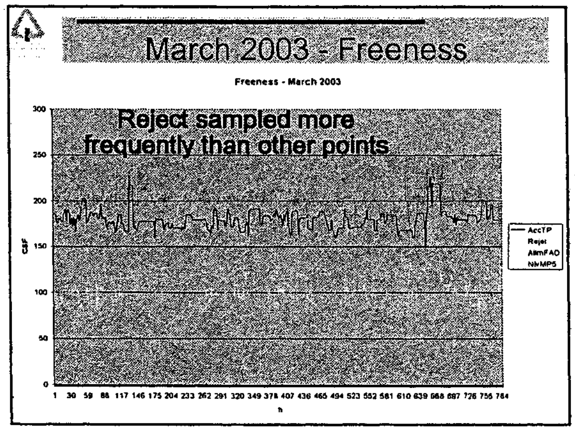
March 2003 – Consistance (calcul)

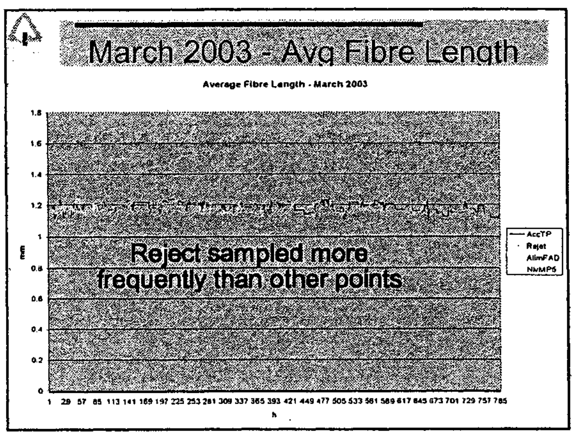


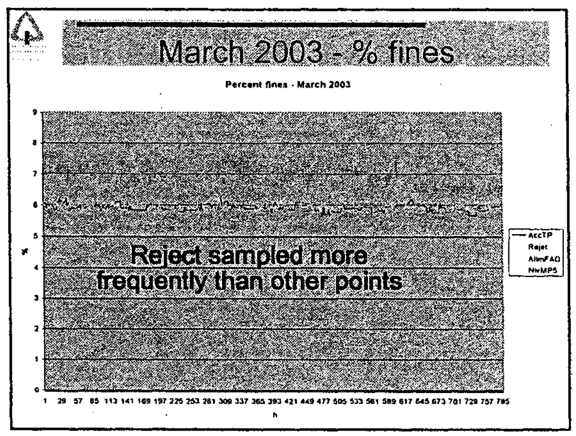
March 2003 – Ecart type charges
(en excluant les arrêts et départs)

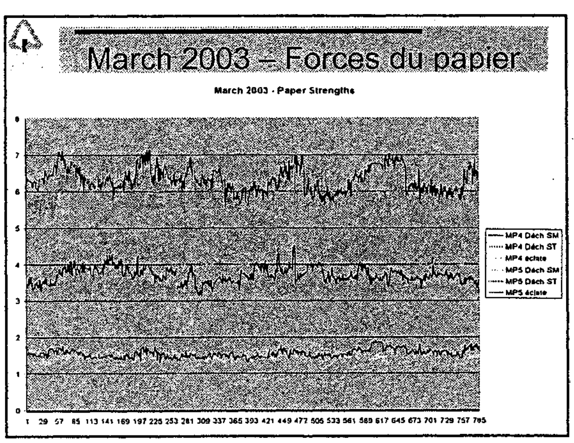


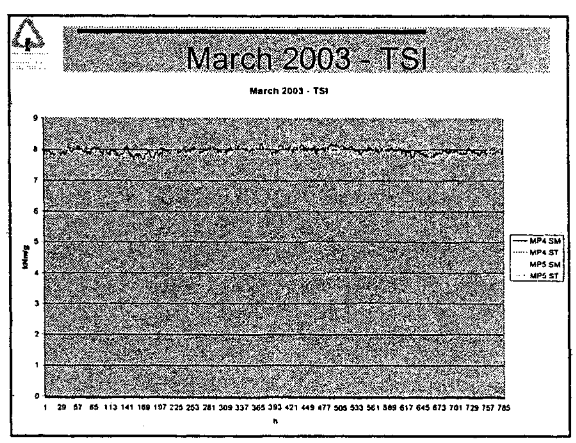

March 2003 – Âge des plaques
Plate age - March 2003
4 plate changes
No plate changes in 1°


March 2003 - Freeness
Freeness - March 2003
Reject sampled more frequently than other points

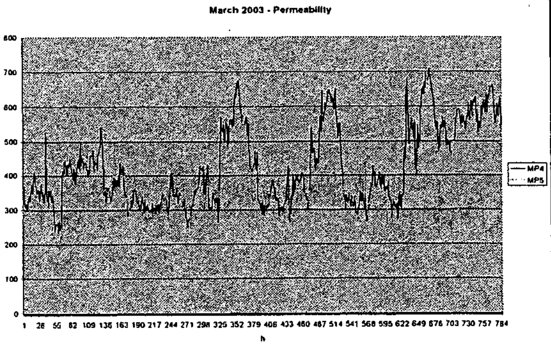

March 2003 - Avg Fibre Length
Average Fibre Length - March 2003
Reject sampled more frequently than other points


March 2003 - % fines
Percent fines - March 2003
Reject sampled more frequently than other points


March 2003 – Forces du papier
March 2003 - Paper Strengths


March 2003 - TSI
March 2003 - TSI

March 2003 - Perméabilité



March 2003 - Peluchage

- No data for this month

Definitive runs/1_graphs

ÉCOLE POLYTECHNIQUE MONTRÉAL

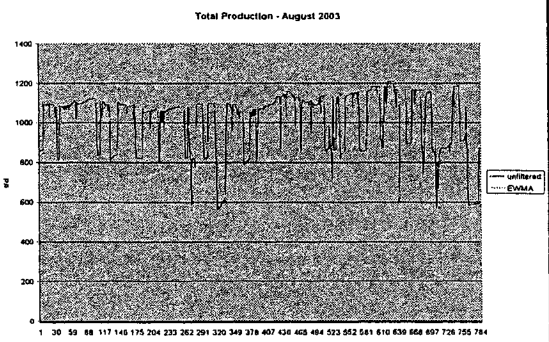
August 2003

- Data pre-treatment
- PCA outliers removed
  - Score Plot
  - Distance-to-model
- EWMA with $\alpha = 0.8$

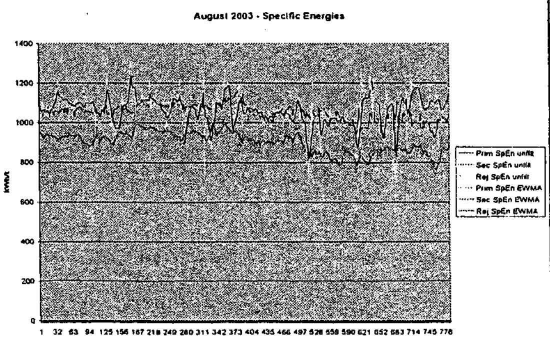
The « Big Grid »: *a.k.a. Overall Experimental Design*

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

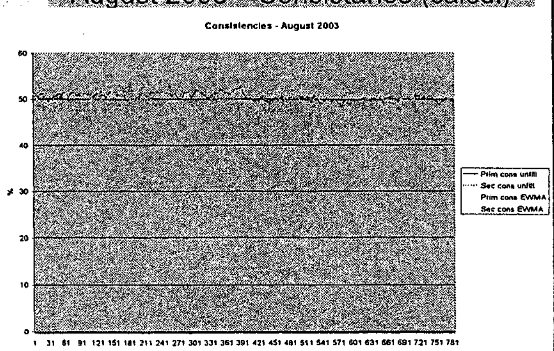
August 2003 – Production 4 lignes



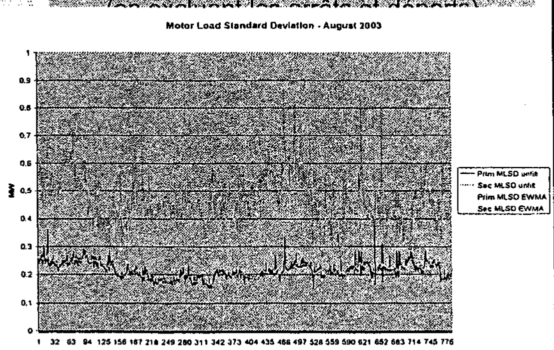
August 2003 – Énergies spécifiques

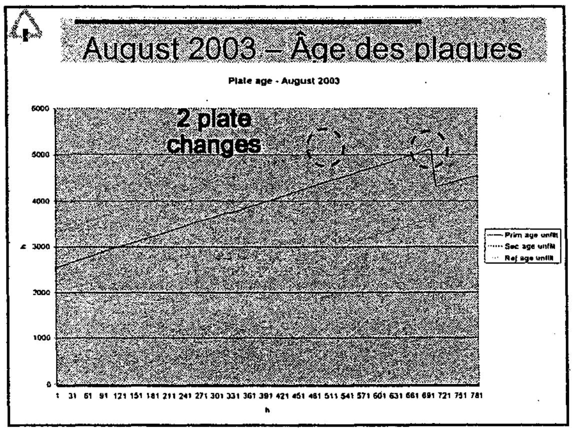


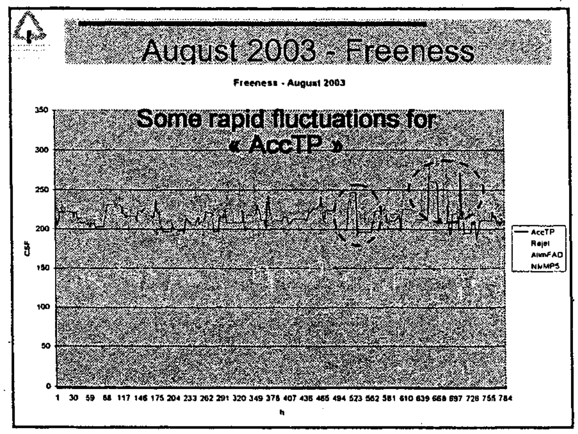
August 2003 – Consistance (calcul)

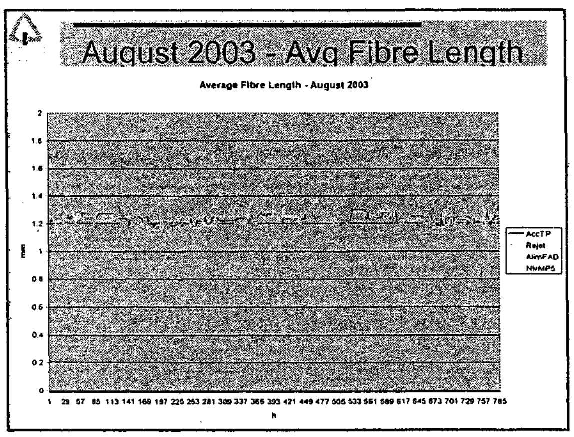


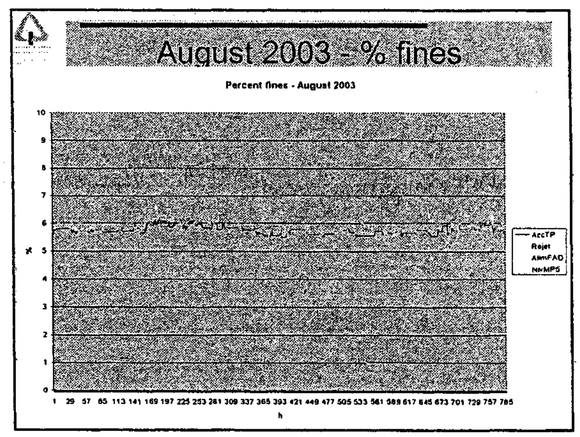
August 2003 – Ecart type charges

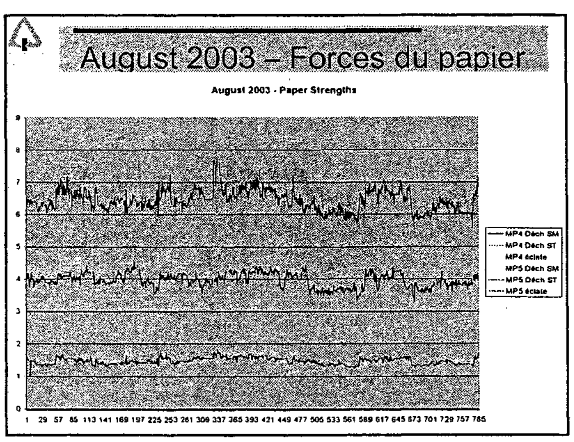


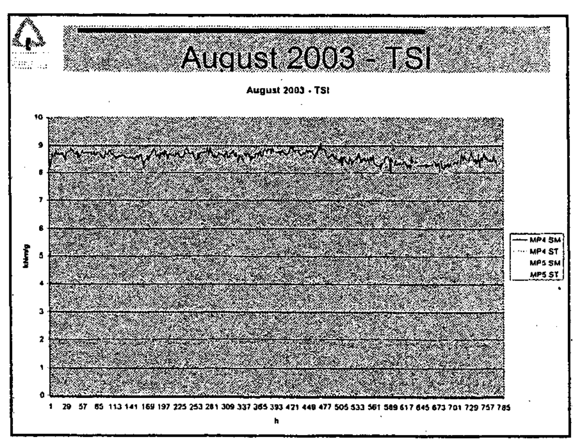

August 2003 – Âge des plaques
Plate age - August 2003
2 plate
changes


August 2003 - Freeness
Freeness - August 2003
Some rapid fluctuations for
« AccTP »
AccTP
Rejet
AlimFAO
NivMP5

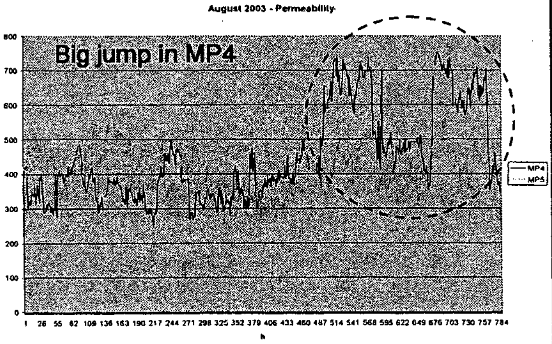

August 2003 - Avg Fibre Length
Average Fibre Length - August 2003
AccTP
Rejet
AlimFAO
NivMP5


August 2003 - % fines
Percent fines - August 2003
AccTP
Rejet
AlimFAO
NivMP5


August 2003 – Forces du papier
August 2003 - Paper Strengths


August 2003 - TSI
August 2003 - TSI
MP4 SM
MP4 ST
MP5 SM
MP5 ST

August 2003 - Perméabilité



August 2003 - Peluchage

- No data for this month

Definitive runs/2_graphs

ÉCOLE POLYTECHNIQUE MONTRÉAL

March 2004

- Data pre-treatment
- PCA outliers removed
  - Score Plot
  - Distance-to-model
- EWMA with α = 0.8

Definitive runs/3_graphs

ÉCOLE POLYTECHNIQUE MONTRÉAL

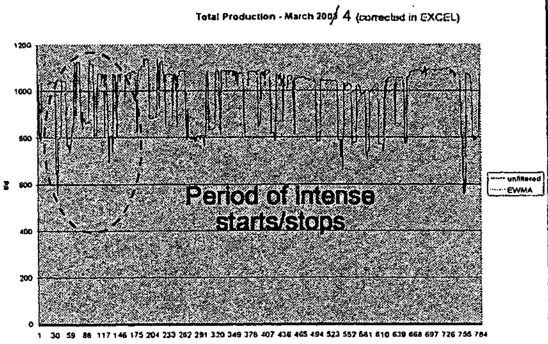
The « Big Grid »: *a.k.a. Overall Experimental Design*

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

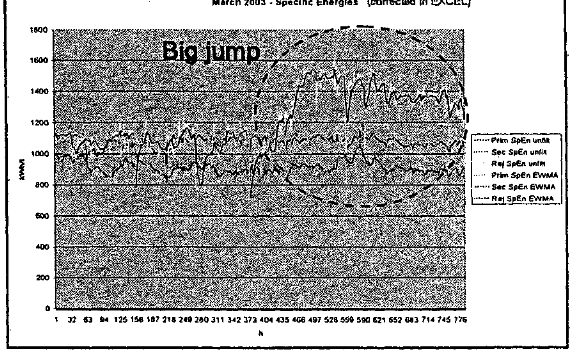
Definitive runs/3_graphs

ÉCOLE POLYTECHNIQUE MONTRÉAL

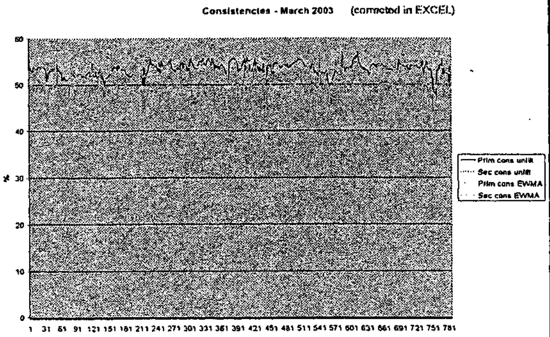
March 2004 – Production 4 lignes



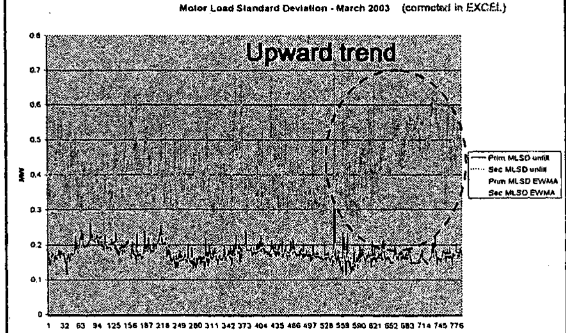
March 2004 – Énergies spécifiques

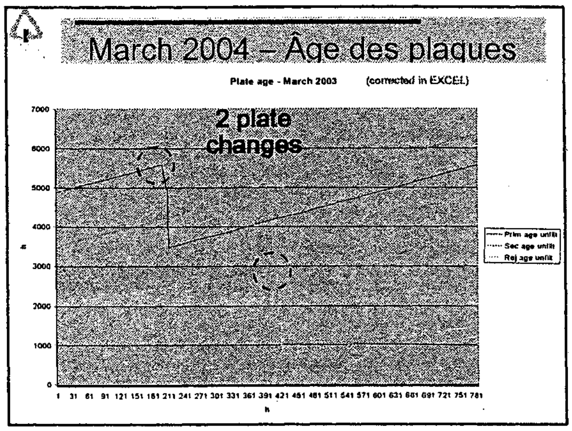


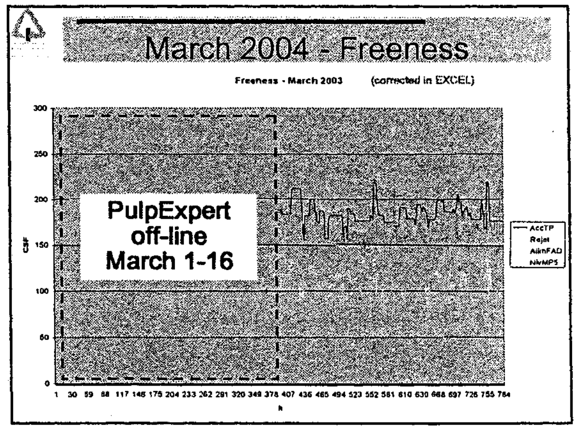
March 2004 – Consistance (calcul)

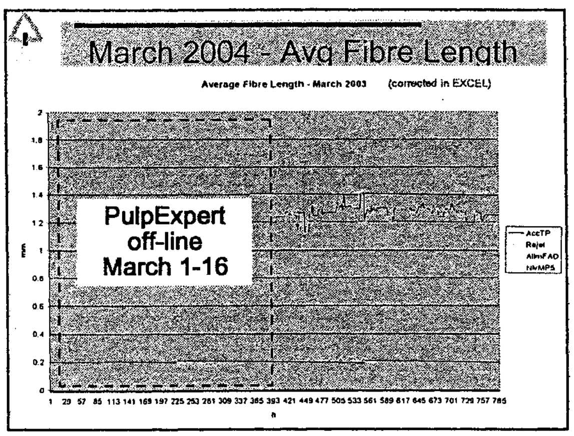


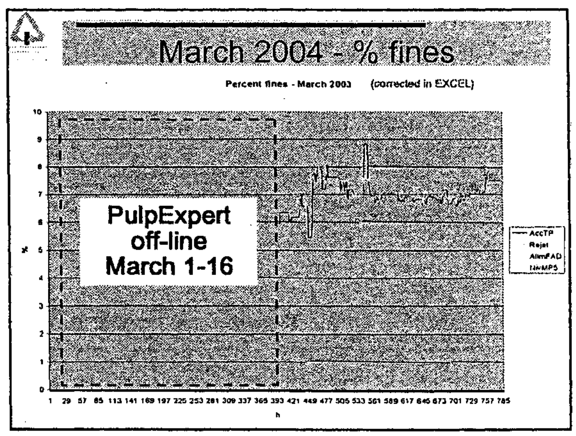
March 2004 – Ecart type charges

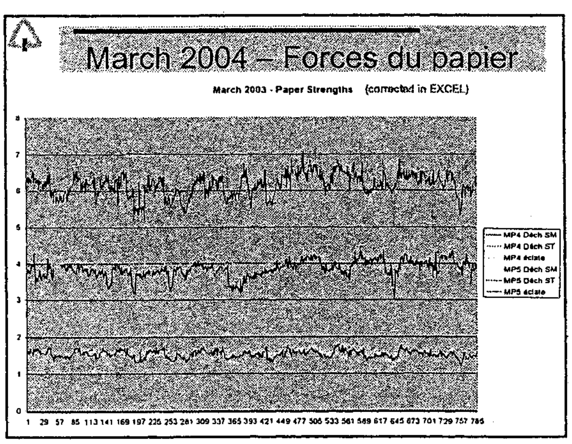


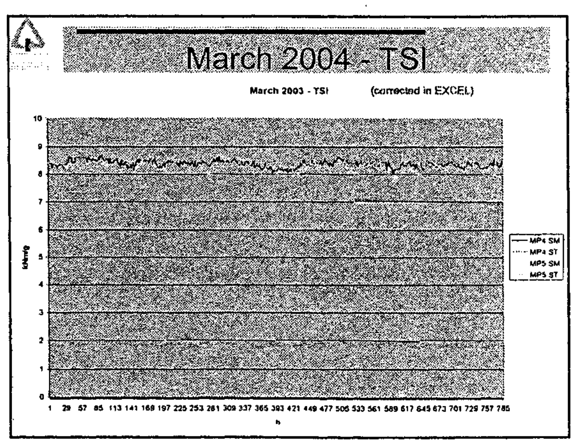

March 2004 – Âge des plaques
Plate age - March 2003 (corrected in EXCEL)
2 plate changes


March 2004 - Freeness
Freeness - March 2003 (corrected in EXCEL)
PulpExpert off-line March 1-16

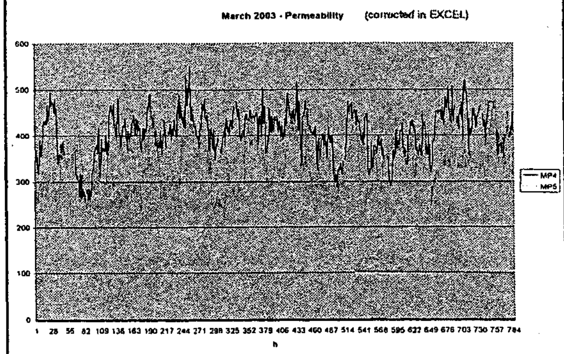

March 2004 - Avg Fibre Length
Average Fibre Length - March 2003 (corrected in EXCEL)
PulpExpert off-line March 1-16


March 2004 - % fines
Percent fines - March 2003 (corrected in EXCEL)
PulpExpert off-line March 1-16


March 2004 – Forces du papier
March 2003 - Paper Strengths (corrected in EXCEL)


March 2004 - TSI
March 2003 - TSI (corrected in EXCEL)

March 2004 - Perméabilité



March 2004 - Peluchage

- No data for this month

Definitive runs/3_graphs

ÉCOLE POLYTECHNIQUE MONTRÉAL

August 2004

- UNIQUE: Only month with data for Linting
- Data pre-treatment
  - PCA outliers removed
    - Score Plot
    - Distance-to-model
  - Only 97 points removed out of 786
    - Thus 689 observations retained
  - EWMA with $\alpha = 0.8$

Definitive runs/4_graphs

ÉCOLE POLYTECHNIQUE MONTRÉAL

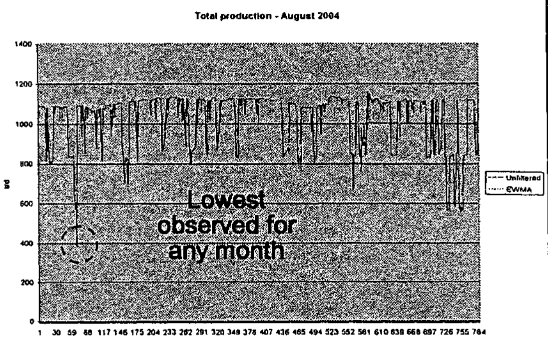
The « Big Grid »: *a.k.a. Overall Experimental Design*

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

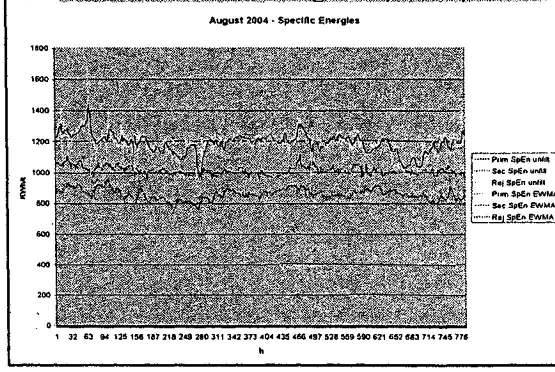
Definitive runs/4_graphs

ÉCOLE POLYTECHNIQUE MONTRÉAL

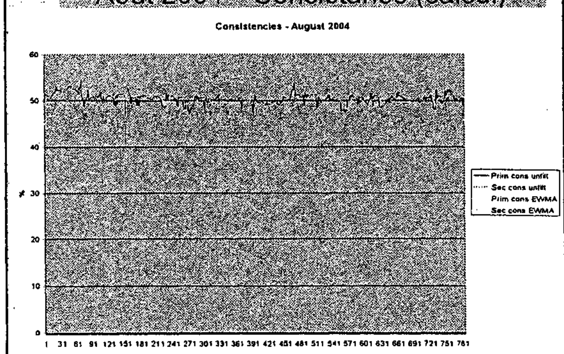
Août 2004 – Production 4 lignes



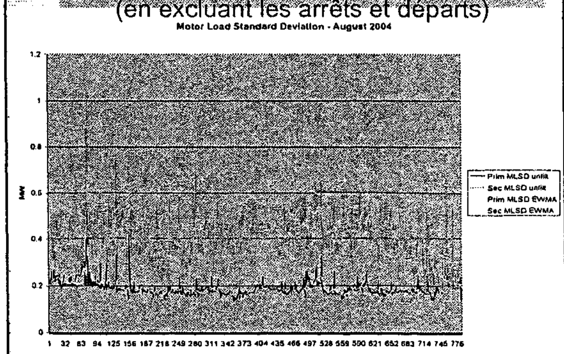
Août 2004 – Energies spécifiques

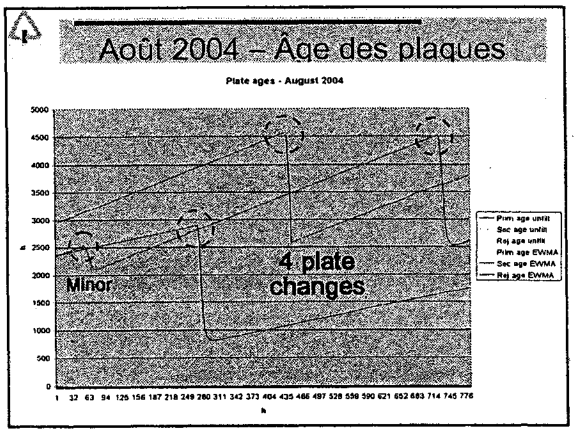


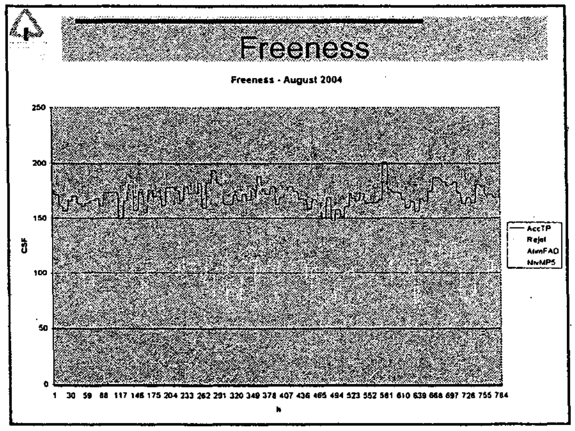
Août 2004 – Consistance (calcul)

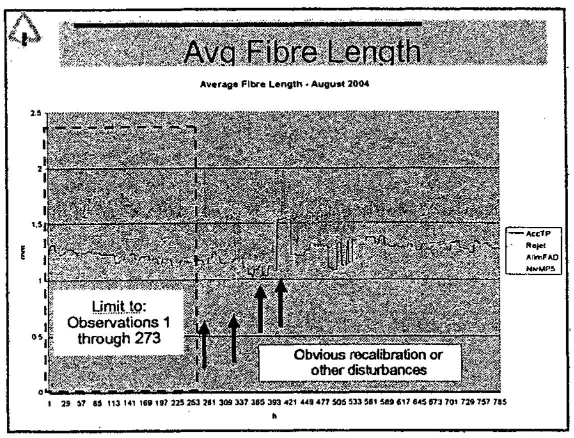


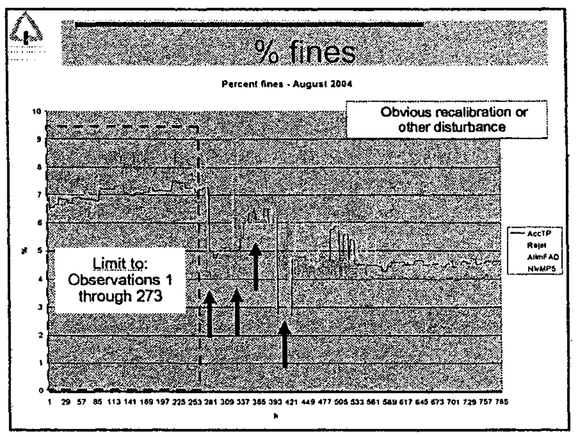
Août 2004 – Ecart type charges (en excluant les arrêts et départs)

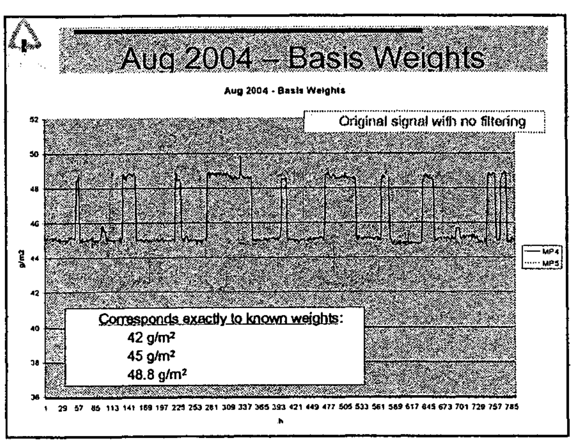


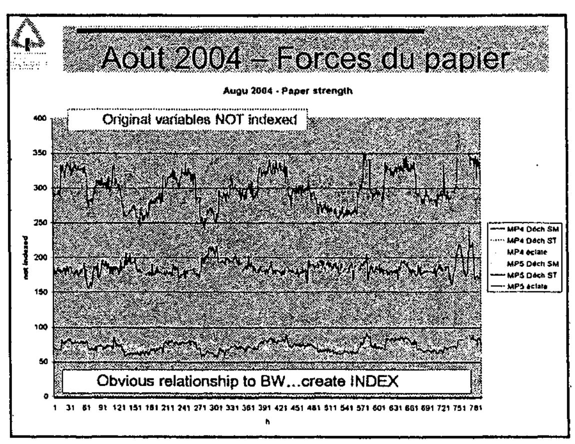

Août 2004 – Âge des plaques
Plate ages - August 2004
Minor
4 plate
changes

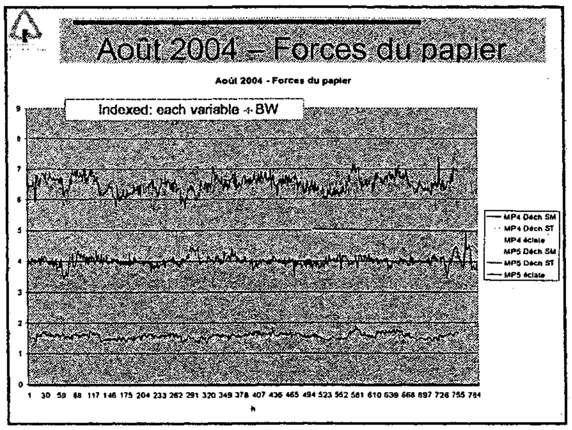

Freeness
Freeness - August 2004
CSF
AccTP
Rejet
AlimFAD
NivMP5

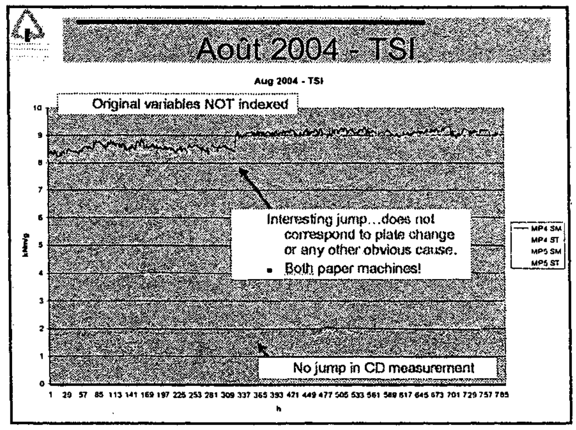

Avg Fibre Length
Average Fibre Length - August 2004
mm
Limit to:
Observations 1
through 273
Obvious recalibration or
other disturbances
AccTP
Rejet
AlimFAD
NivMP5

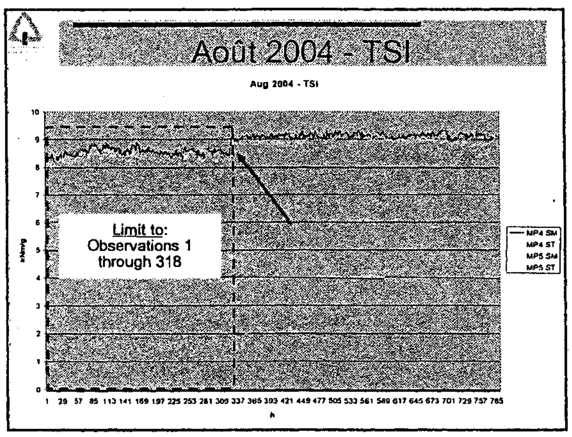

% fines
Percent fines - August 2004
Obvious recalibration or
other disturbance
%
Limit to:
Observations 1
through 273
AccTP
Rejet
AlimFAD
NivMP5

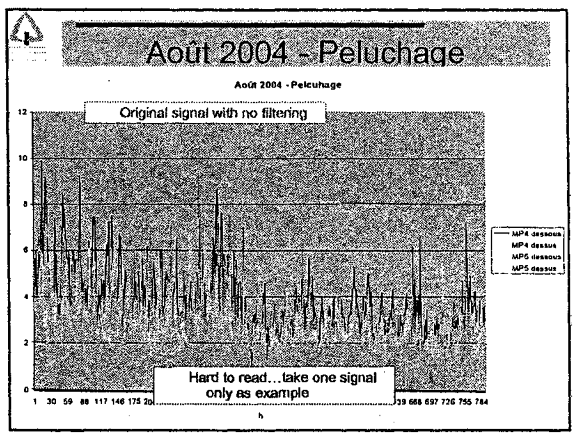

Aug 2004 – Basis Weights
Aug 2004 - Basis Weights
Original signal with no filtering
g/m2
Corresponds exactly to known weights:
42 g/m²
45 g/m²
48.8 g/m²
MP4
MP5

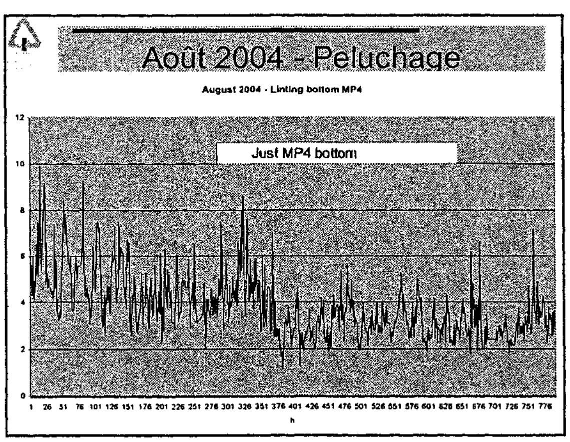

Août 2004 – Forces du papier
Augu 2004 - Paper strength
Original variables NOT indexed
not indexed
Obvious relationship to BW…create INDEX

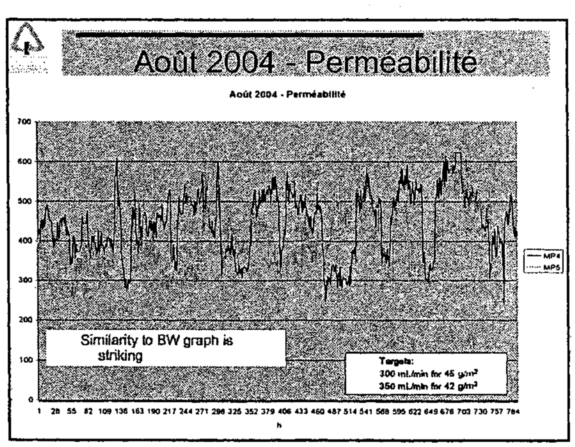

Août 2004 – Forces du papier
Août 2004 - Forces du papier
Indexed: each variable ÷ BW


Août 2004 - TSI
Aug 2004 - TSI
Original variables NOT indexed
Interesting jump…does not correspond to plate change or any other obvious cause.
Both paper machines!
No jump in CD measurement


Août 2004 - TSI
Aug 2004 - TSI
Limit to:
Observations 1 through 318


Août 2004 - Peluchage
Août 2004 - Pelcuhage
Original signal with no filtering
Hard to read…take one signal only as example


Août 2004 - Peluchage
August 2004 - Linting bottom MP4
Just MP4 bottom


Août 2004 - Perméabilité
Août 2004 - Perméabilité
Similarity to BW graph is striking
Targets:
300 mL/min for 45 g/m²
350 mL/min for 42 g/m²

Permeability

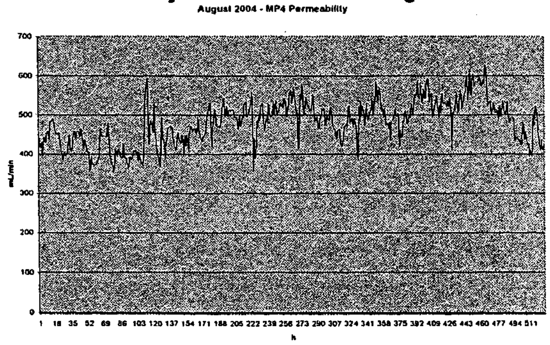
- APPROACH: Separate dataset into subsets based on BW
  - For example: for MP4, use only hours where BW was equal to 45 g/m²

Definitive runs/4_graphs

ÉCOLE POLYTECHNIQUE MONTRÉAL

August 2004 – MP4 Permeability

Only hours where BW = 45 g/m²



The « Big Grid »:
a.k.a. Overall Experimental Design

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej +	AlimFAD	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Definitive runs/1-1

ECOLE POLYTECHNIQUE MONTREAL

1-1-A

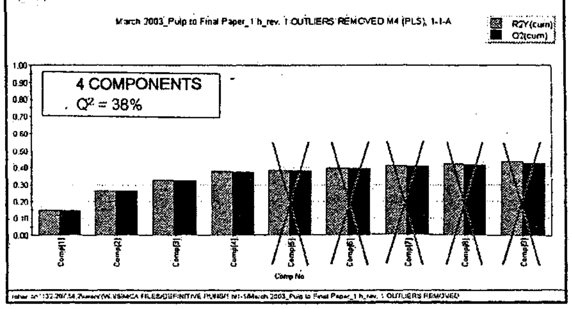
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej +	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use entire month

Definitive runs/1-1

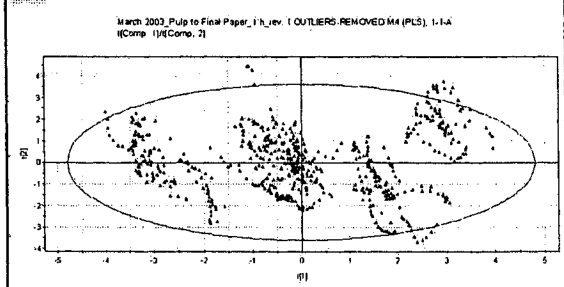
ECOLE POLYTECHNIQUE MONTREAL

1-1-A



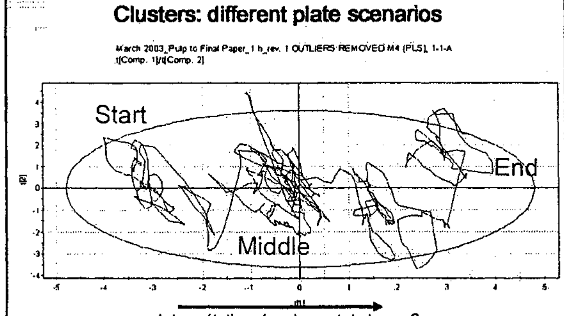
1-1-A

Clusters: different plate scenarios



1-1-A

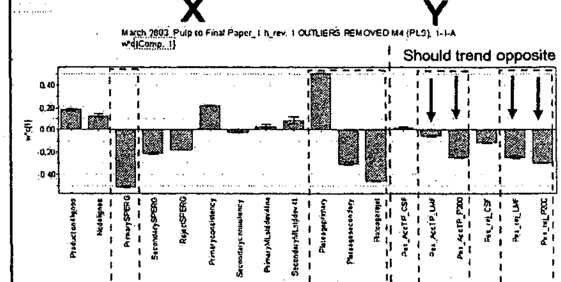
Clusters: different plate scenarios

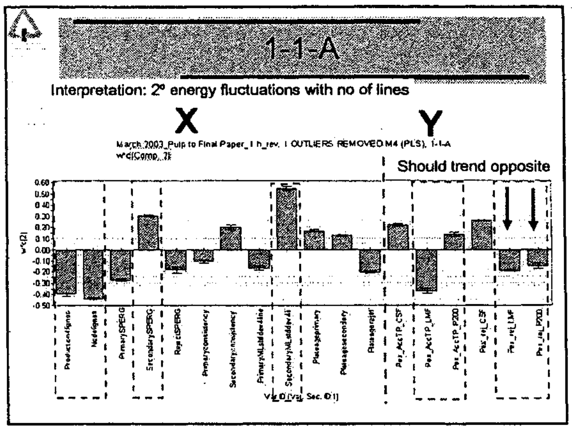


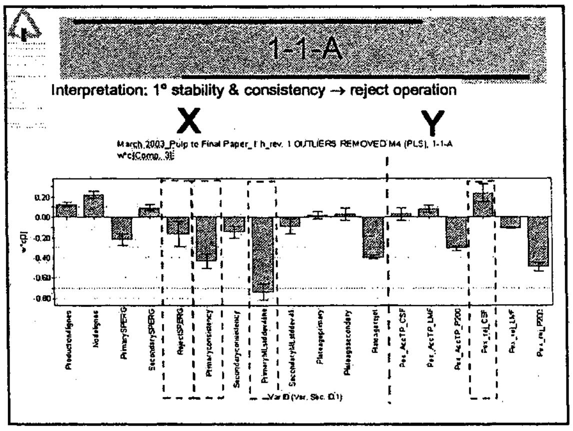
Interprétation: écoulement du temps?

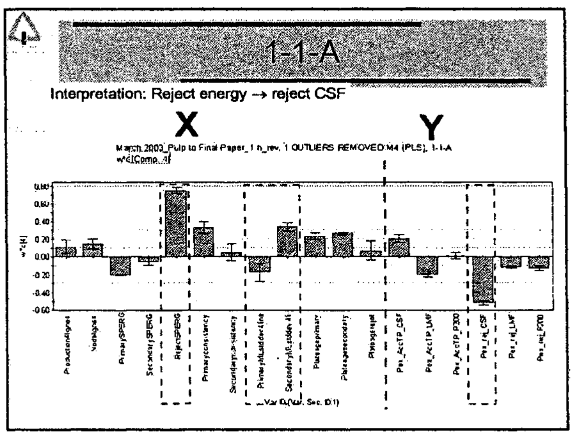
1-1-A

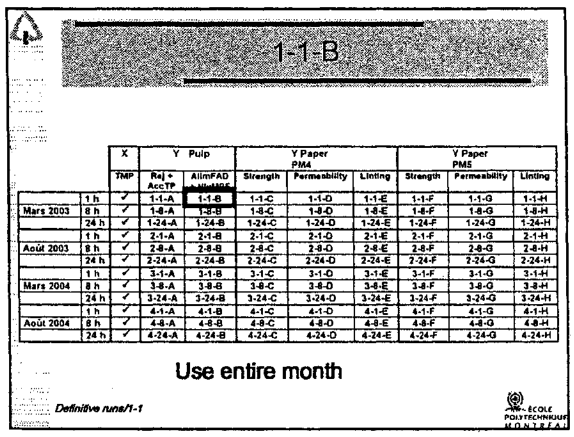
Interpretation: gradual wear of 1° plates











		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use entire month

Definitive runs/1-1

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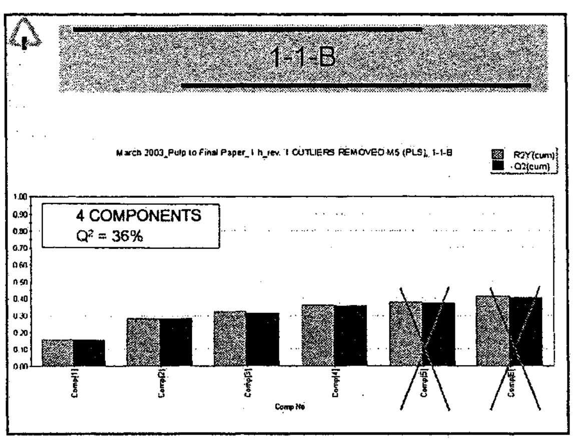
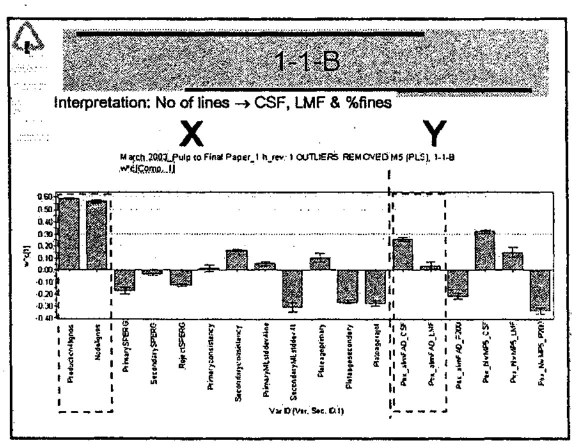
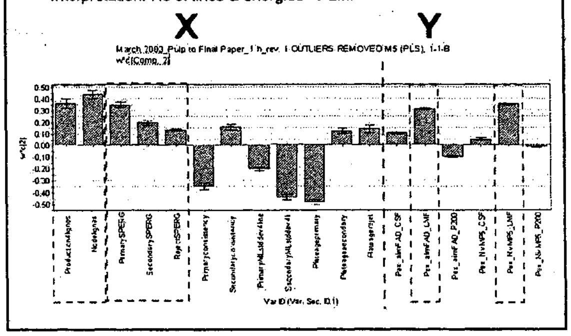




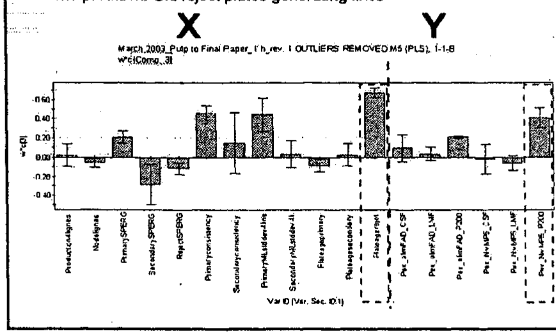
1-1-B

Interpretation: No of lines & energies → LMF



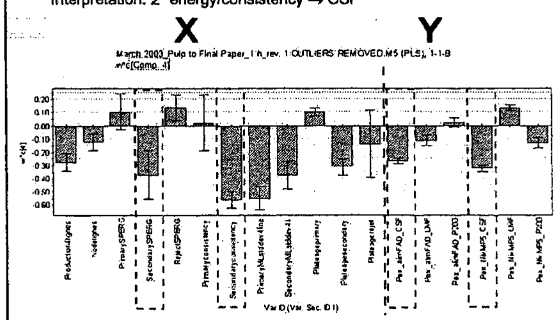
1-1-B

Interpretation: Old reject plates generating fines



1-1-B

Interpretation: 2° energy/consistency → CSF



1-1-C

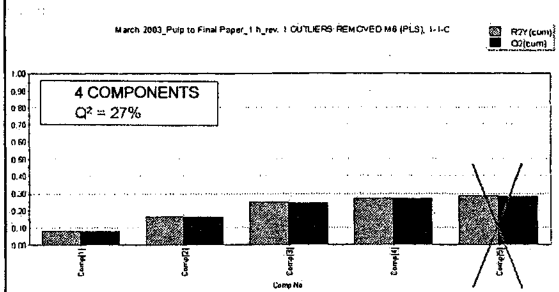
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use entire month

Definitive runs/1-1

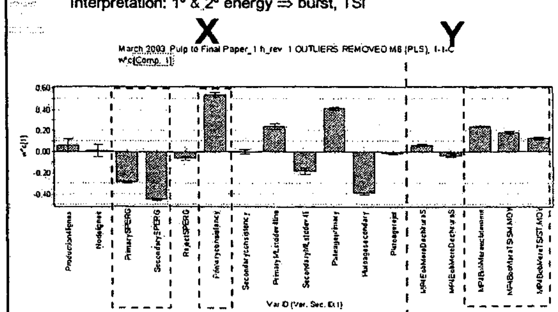
ÉCOLE POLYTECHNIQUE MONTRÉAL

1-1-C



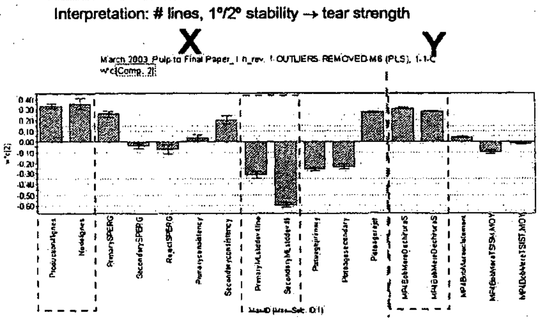
1-1-C

Interpretation: 1° & 2° energy ⇒ burst, TSI



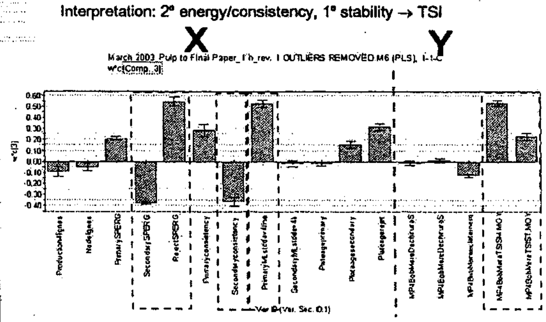
1-1-C

Interpretation: # lines, 1°/2° stability → tear strength



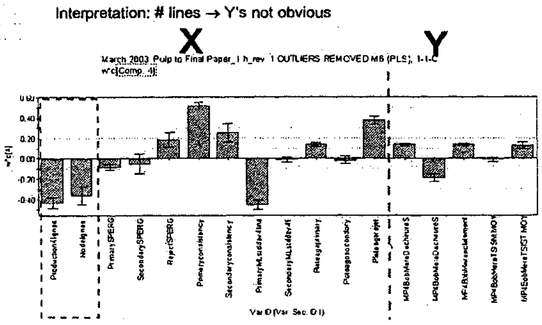
1-1-C

Interpretation: 2° energy/consistency, 1° stability → TSI



1-1-C

Interpretation: # lines → Y's not obvious



1-1-D

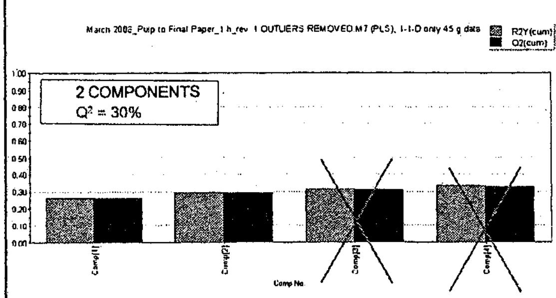
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use only hours where Basis Weight = 45 g/m²

Definitive runs/1-1

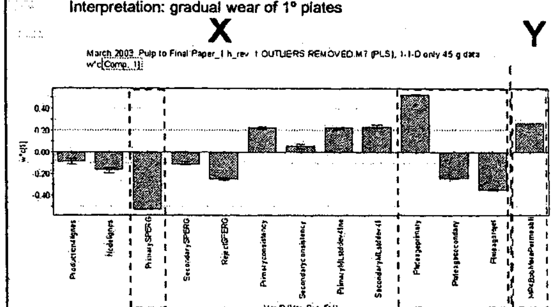
ÉCOLE POLYTECHNIQUE MONTRÉAL

1-1-D



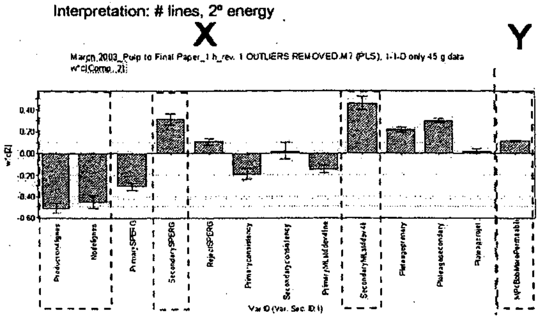
1-1-D

Interpretation: gradual wear of 1° plates



1-1-D

Interpretation: # lines, 2e energy



1-1-E

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Definitive runs/1-1

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1-1-E

- No data for this month

Definitive runs/1-1

ECOLE POLYTECHNIQUE MONTREAL

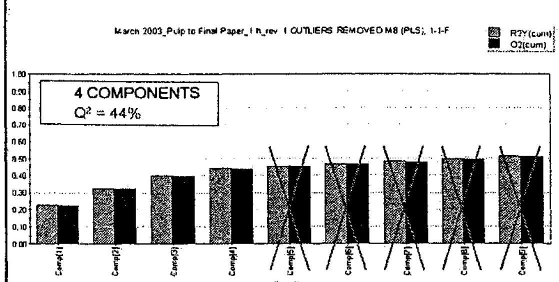
1-1-F

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Definitive runs/1-1

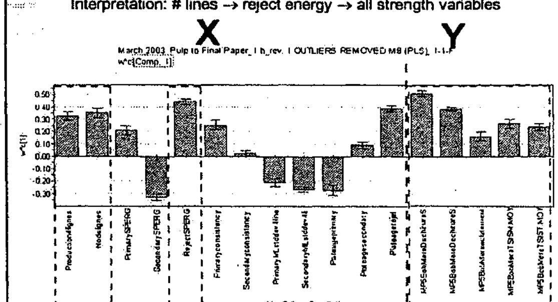
ECOLE POLYTECHNIQUE MONTREAL

1-1-F



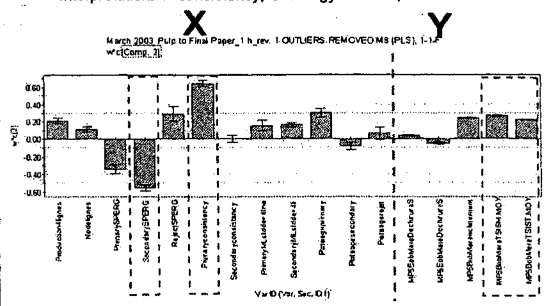
1-1-F

Interpretation: # lines → reject energy → all strength variables



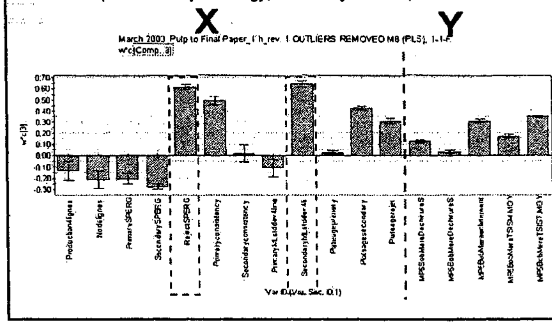
1-1-F

Interpretation: 1° consistency, 2° energy → Burst, TSI



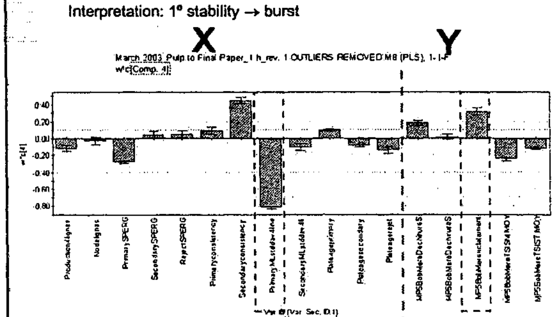
1-1-F

Interpretation: Reject energy, 2° stability → Burst, TSI



1-1-F

Interpretation: 1° stability → burst



1-1-G

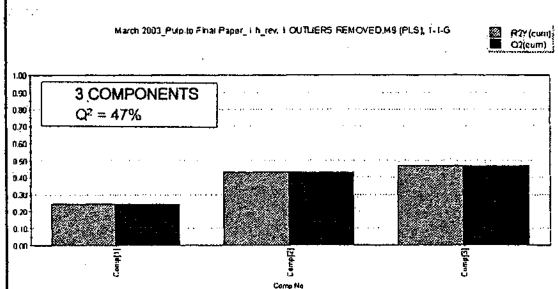
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	$\boxed{\text{1-1-G}}$	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use only hours where Basis Weight = 45 g/m^2

Definitive runs/1-1

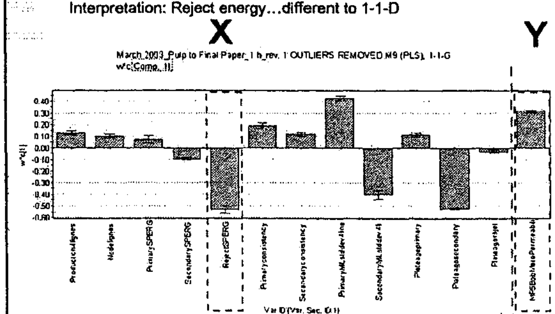
ECOLE POLYTECHNIQUE MONTREAL

1-1-G



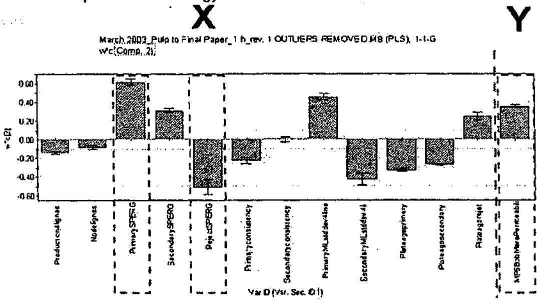
1-1-G

Interpretation: Reject energy…different to 1-1-D



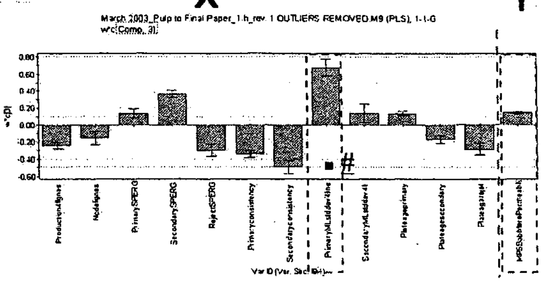
1-1-G

Interpretation: 1° energy



1-1-G

Interpretation: 1° stability



1-1-H

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Definitive runs/1-1

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1-1-H

- No data for this month

Definitive runs/1-1

ECOLE POLYTECHNIQUE MONTREAL

The « Big Grid »: *a.k.a. Overall Experimental Design*

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Definitive runs/1-1

ÉCOLE POLYTECHNIQUE MONTRÉAL

2-1-A

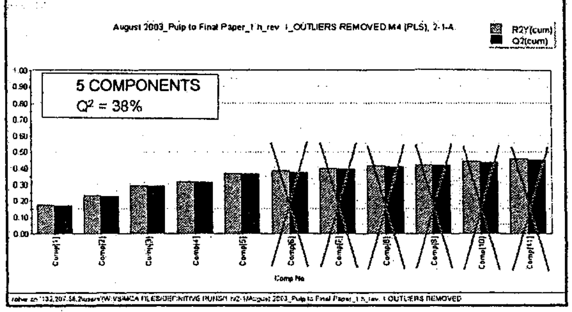
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use all hours

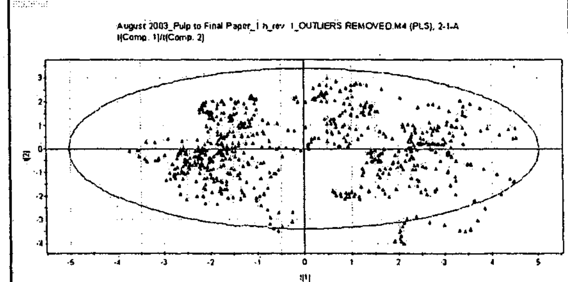
Definitive runs/1-1

ÉCOLE POLYTECHNIQUE MONTRÉAL

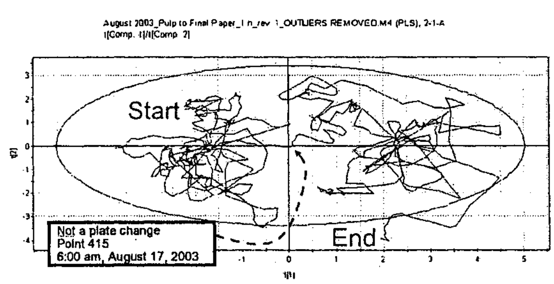
2-1-A



2-1-A

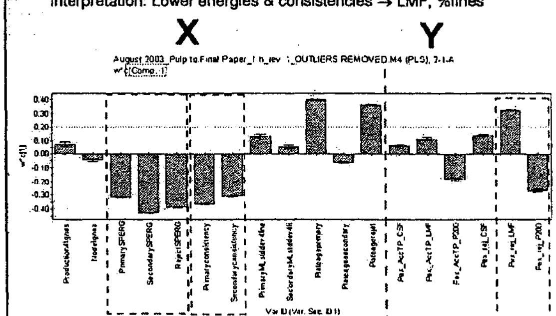


2-1-A



2-1-A

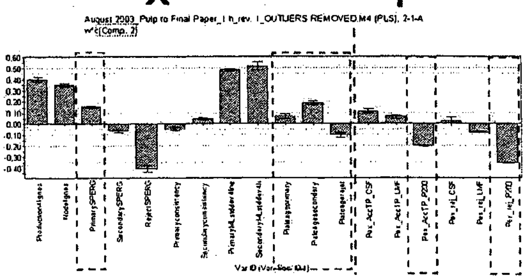
Interpretation: Lower energies & consistencies → LMF, %fines



2-1-A

Interpretation: # lines & 1°/2° stability → %fines

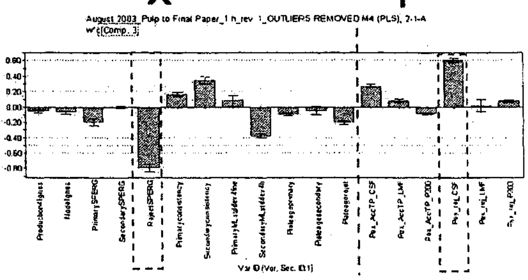
X Y



2-1-A

Interpretation: Reject energy → CSF

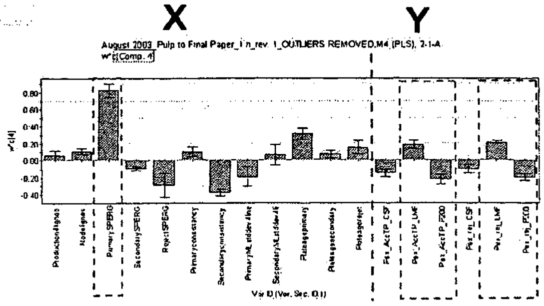
X Y



2-1-A

Interpretation: 1° energy → LMF, %fines

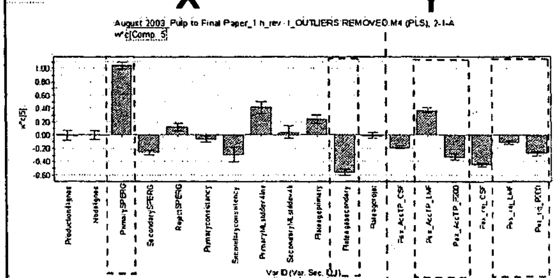
X Y



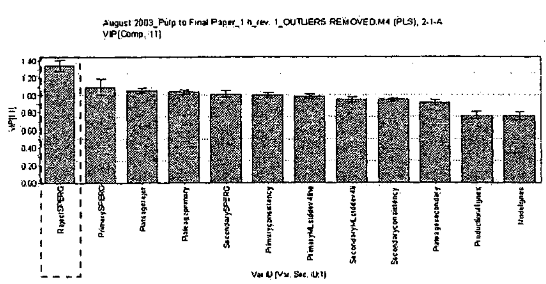
2-1-A

Interpretation: Echo of component 4? Only with new 2° plates

X Y



2-1-A



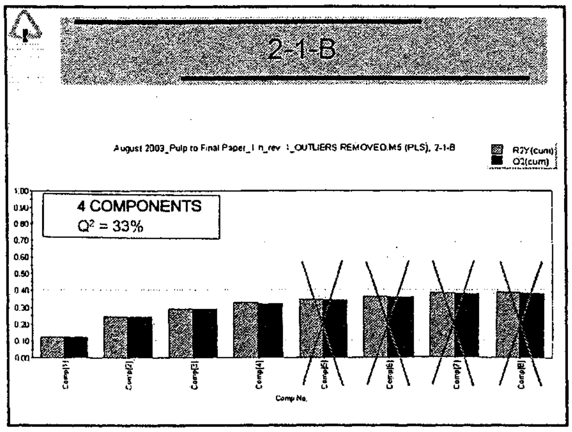
2-1-B

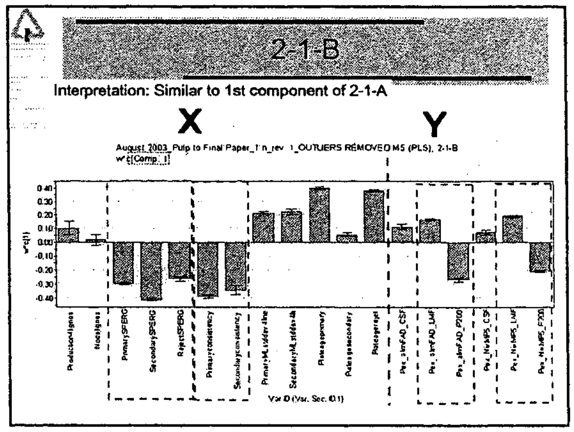
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	$\boxed{\text{2-1-B}}$	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

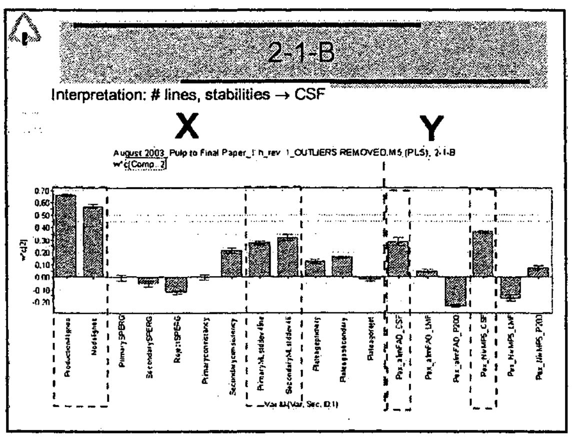
Use all hours

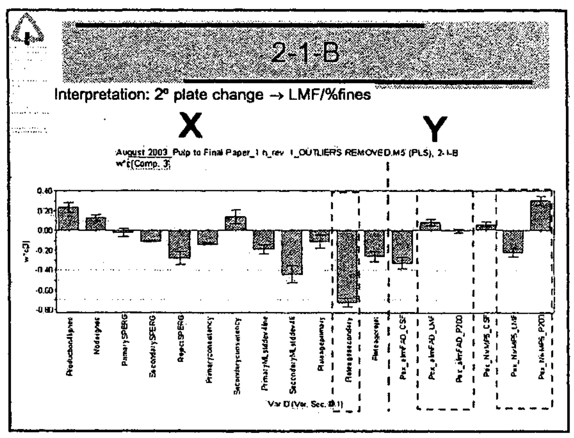
Definitive runs/1-1

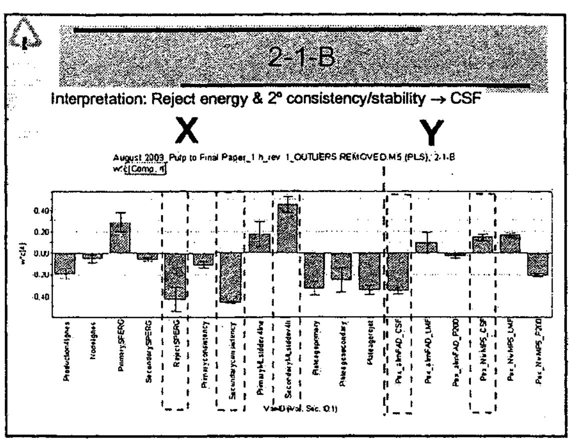
ECOLE POLYTECHNIQUE MONTREAL











2-1-C

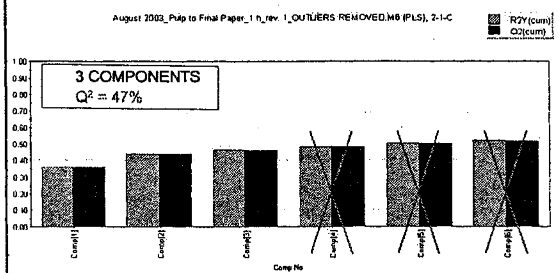
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	$\boxed{\text{2-1-C}}$	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use entire month

Definitive runs/1-1

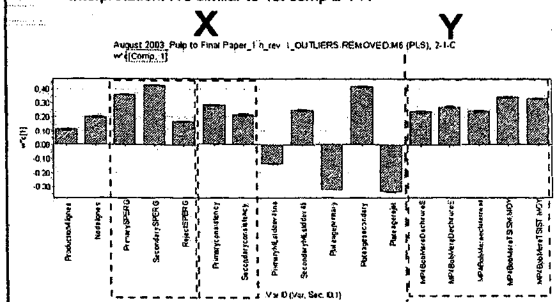
ÉCOLE POLYTECHNIQUE MONTRÉAL

2-1-C



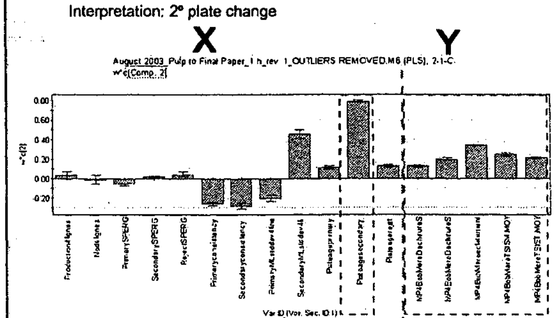
2-1-C

Interpretation: X's similar to 1st comp 2-1-A



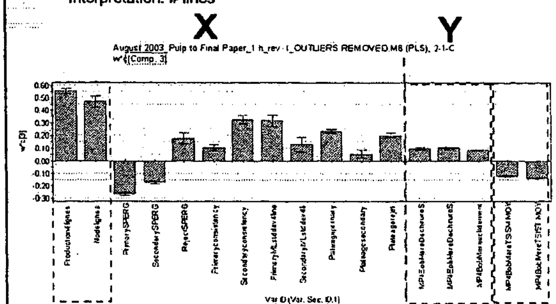
2-1-C

Interpretation: 2e plate change

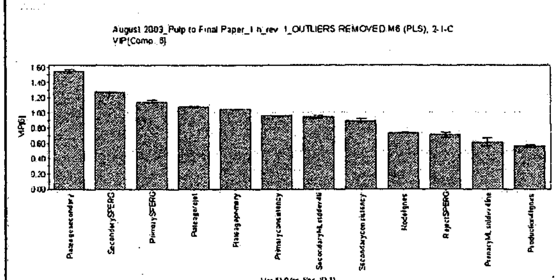


2-1-C

Interpretation: # lines



2-1-C



2-1-D

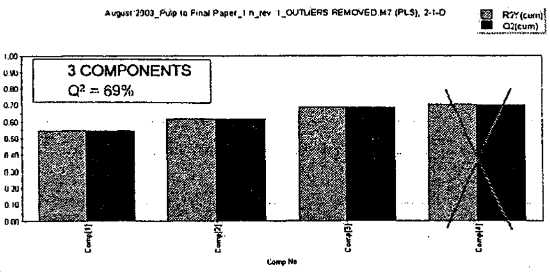
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use only hours where Basis Weight = 45 g/m²

Definitive runs/1-1

ÉCOLE POLYTECHNIQUE MONTRÉAL

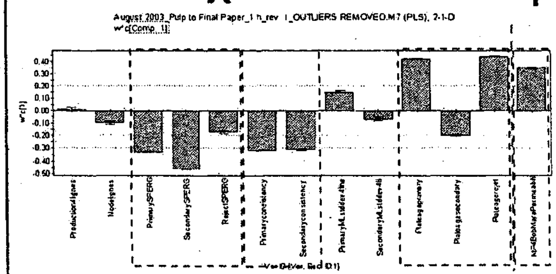
2-1-D



2-1-D

Interpretation: Similar to 1st comp 2-1-A

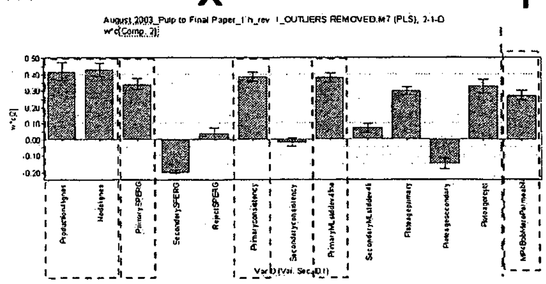
X Y



2-1-D

Interpretation: # lines, 1° energy/consistency/instability

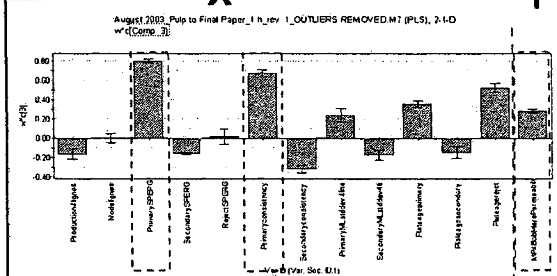
X Y



2-1-D

Interpretation: just 1° energy/consistency

X Y



2-1-E

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	$\boxed{\text{2-1-E}}$	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Definitive runs/1-1

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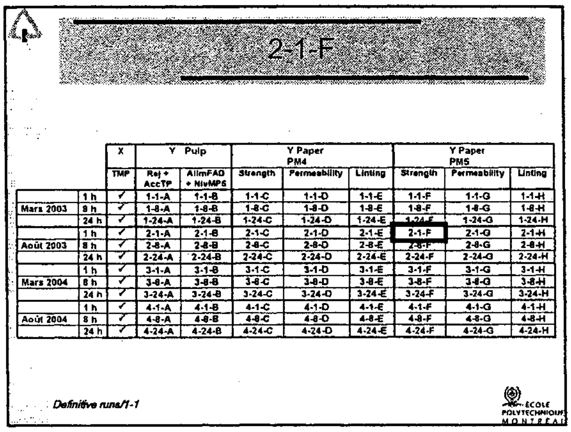
2-1-E

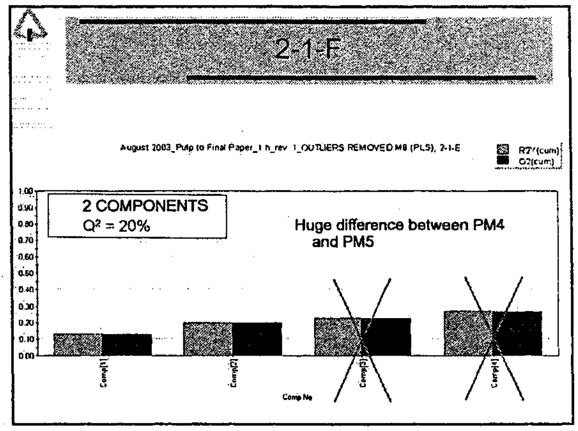
- No data for this month

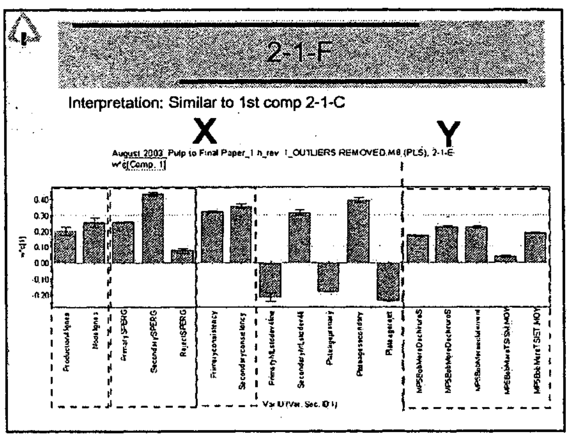
Definitive runs/1-1

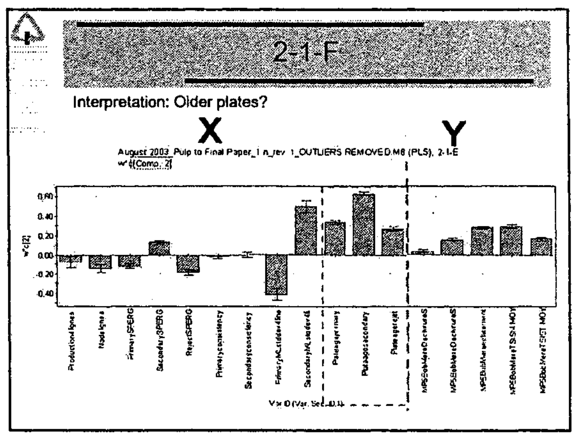
ÉCOLE POLYTECHNIQUE MONTRÉAL

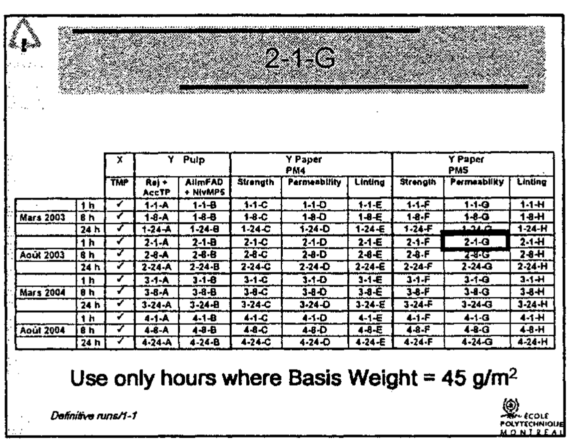


		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	$\boxed{\text{2-1-F}}$	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

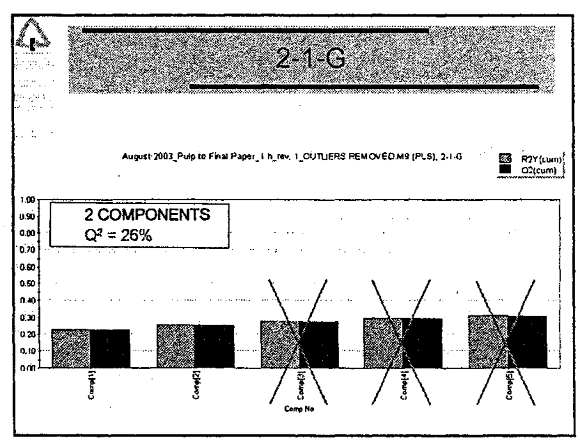






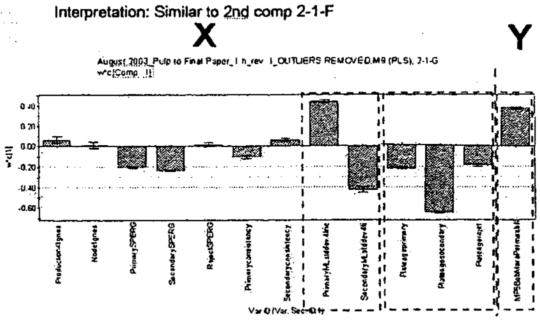


		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	$\boxed{\text{2-1-G}}$	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H



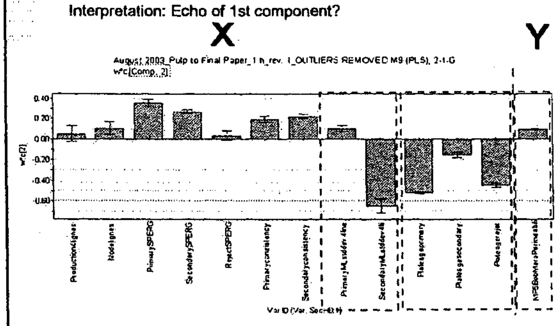
2-1-G

Interpretation: Similar to 2nd comp 2-1-F



2-1-G

Interpretation: Echo of 1st component?



2-1-H

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAO + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	$\boxed{\text{2-1-H}}$
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Definitive runs/1-1

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2-1-H

- No data for this month

Definitive runs/1-1

ÉCOLE POLYTECHNIQUE MONTRÉAL

The « Big Grid »: a.k.a. Overall Experimental Design

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Definitive runs/3-1

ÉCOLE POLYTECHNIQUE MONTRÉAL

3-1-A

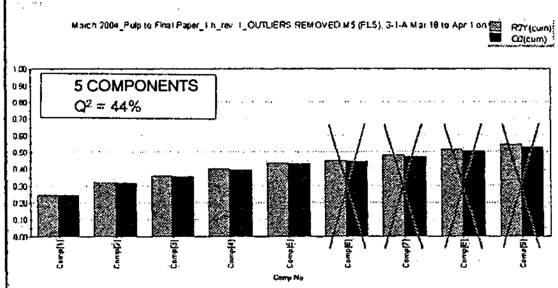
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use only March 18 to April 1 (PulpExpert malfunction)

Definitive runs/3-1

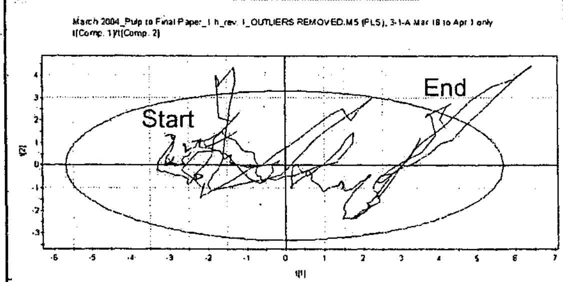
ÉCOLE POLYTECHNIQUE MONTRÉAL

3-1-A



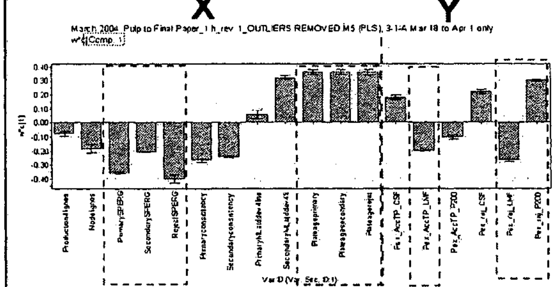
3-1-A

March 18 to April 1 only



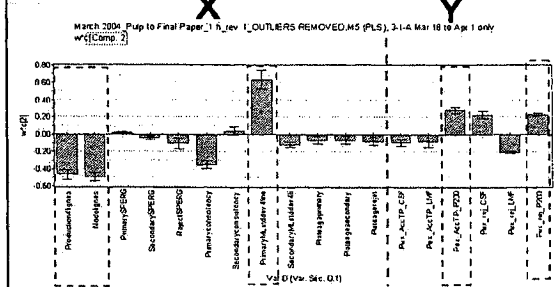
3-1-A

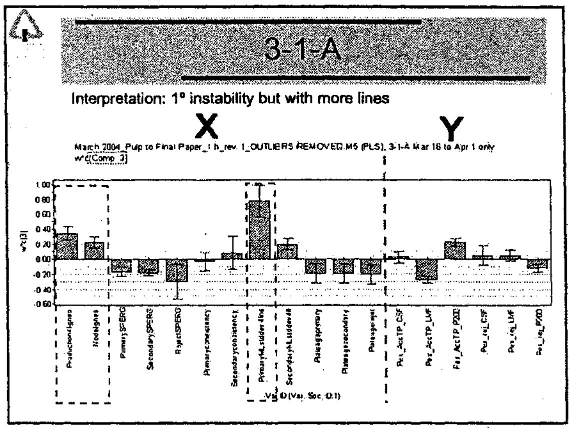
Interpretation: older plates take less energy to produce more fines

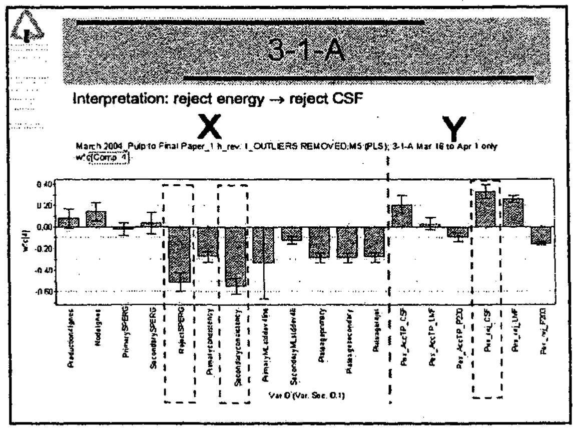


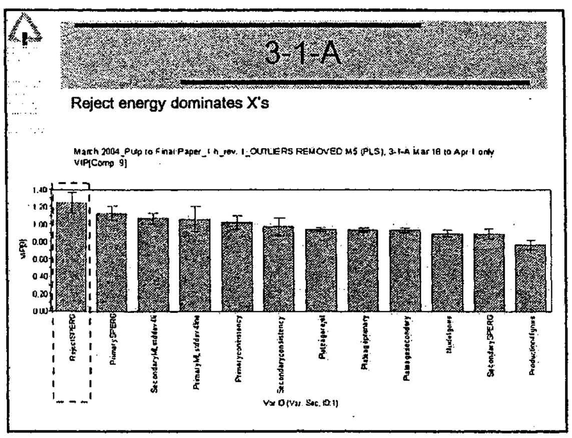
3-1-A

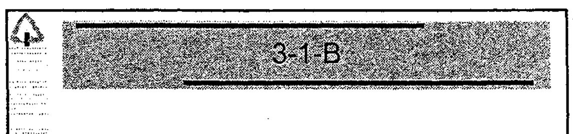
Interpretation: # lines & higher 1° instability → more fines









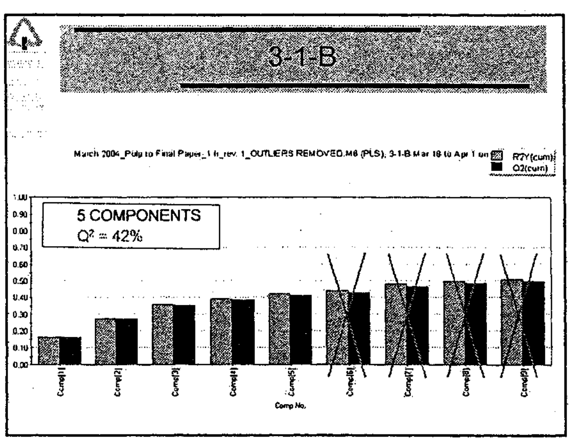


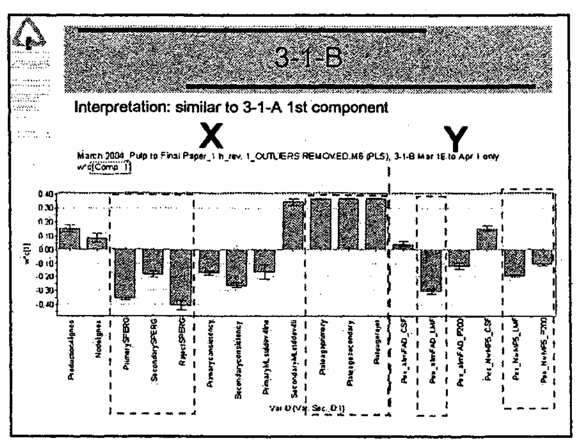
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	~~2-24-B~~	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	$\boxed{3\text{-}1\text{-}B}$	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	~~3-8-B~~	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

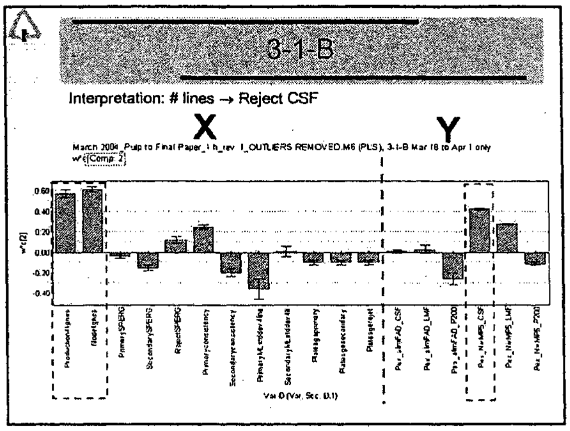
Use only March 18 to April 1

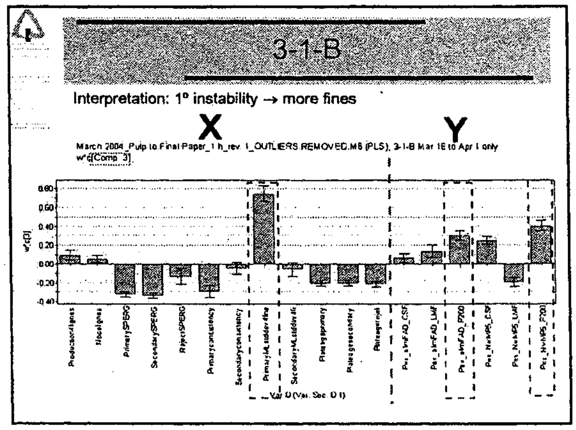
Definitive runs/3-1

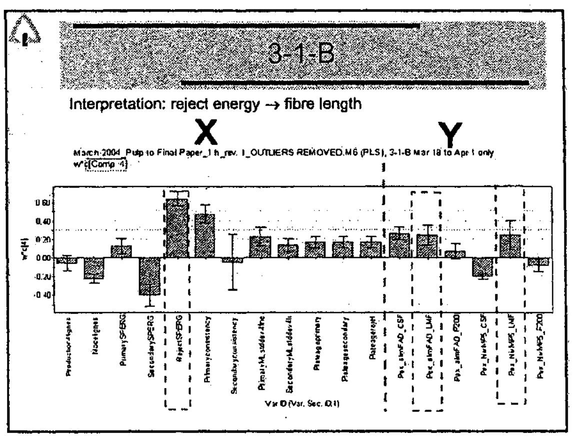
ÉCOLE POLYTECHNIQUE MONTRÉAL

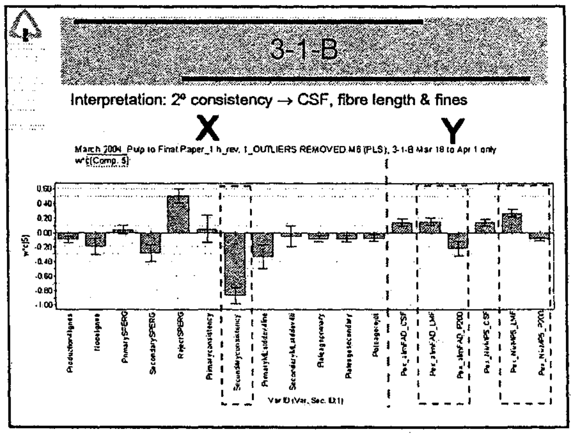












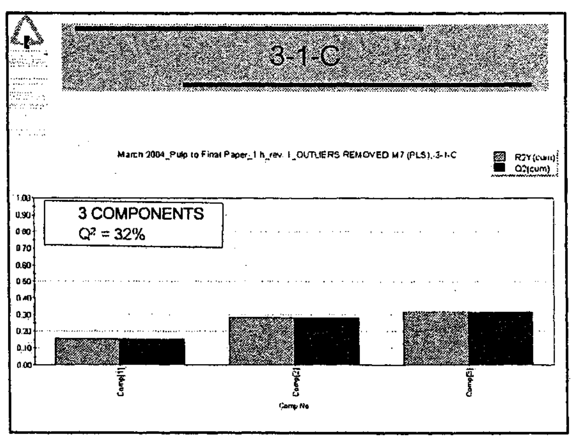
3-1-C

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP6	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	$\boxed{\text{3-1-C}}$	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use entire month

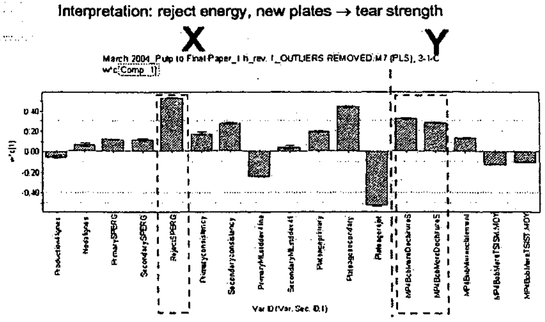
Definitive runs/3-1

ÉCOLE POLYTECHNIQUE MONTRÉAL



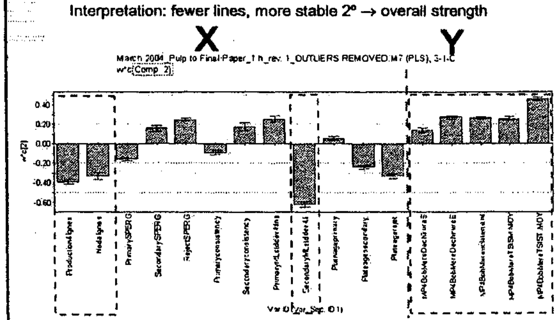
3-1-C

Interpretation: reject energy, new plates → tear strength



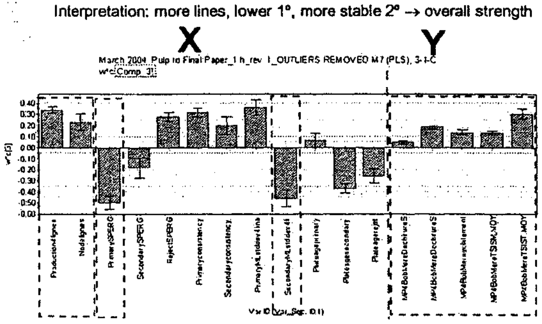
3-1-C

Interpretation: fewer lines, more stable 2° → overall strength



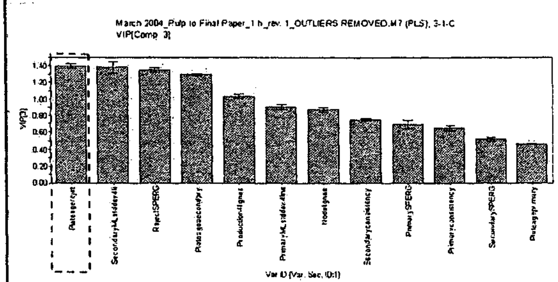
3-1-C

Interpretation: more lines, lower 1°, more stable 2° → overall strength



3-1-C

Reject plate age dominates X's



3-1-D

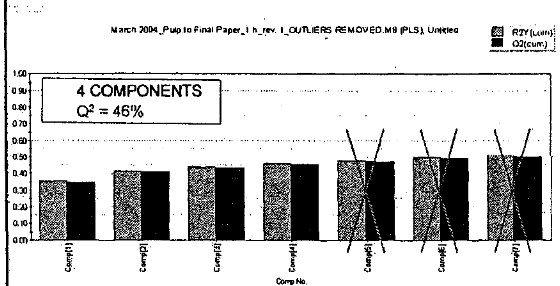
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use only hours where Basis Weight = 45 g/m^2

Definitive runs/3-1

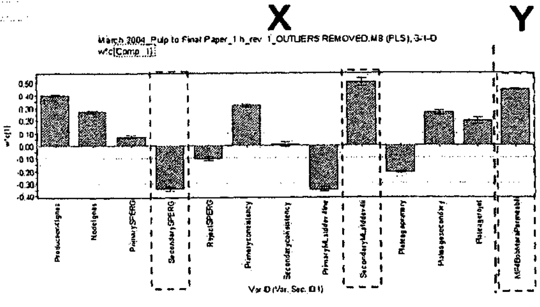
ÉCOLE POLYTECHNIQUE MONTRÉAL

3-1-D



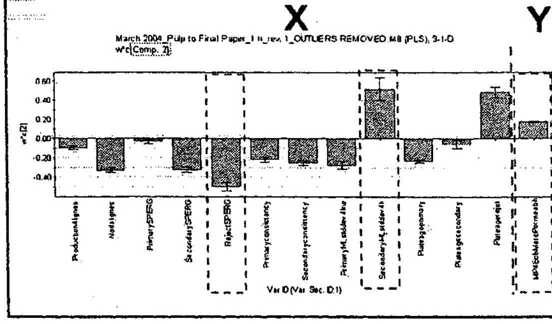
3-1-D

Interpretation: 2° energy, stability → permeability



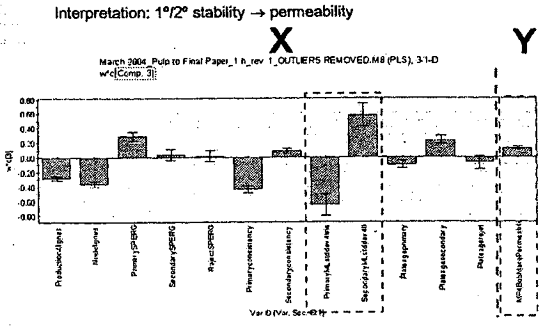
3-1-D

Interpretation: Reject energy, 2° stability → permeability



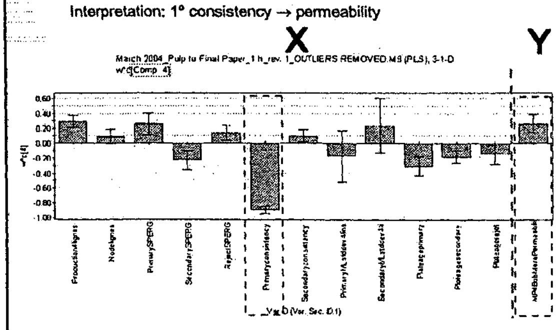
3-1-D

Interpretation: 1°/2° stability → permeability



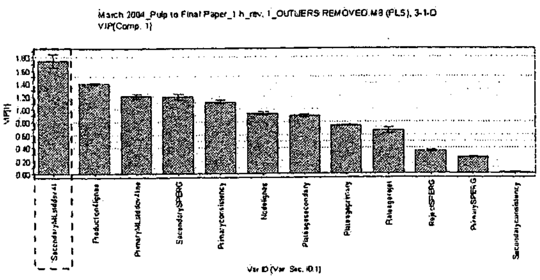
3-1-D

Interpretation: 1° consistency → permeability



3-1-D

2° stability dominates X's



3-1-E

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	$\boxed{\text{3-1-E}}$	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Definitive runs/3-1

ÉCOLE POLYTECHNIQUE MONTRÉAL

3-1-E

- No data for this month

Definitive runs/3-1

ÉCOLE POLYTECHNIQUE MONTRÉAL

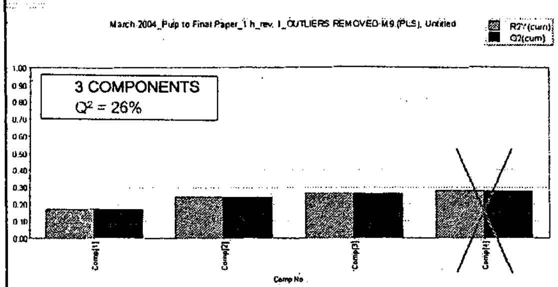
3-1-F

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	$\boxed{3\text{-}1\text{-}F}$	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Definitive runs/3-1

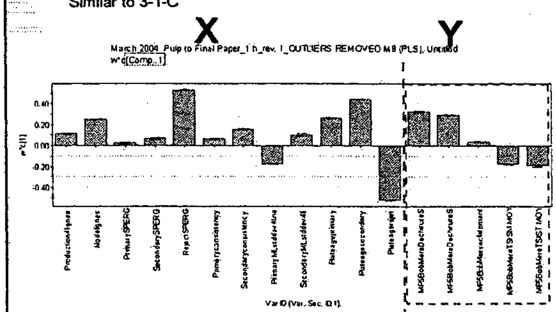
ÉCOLE POLYTECHNIQUE MONTRÉAL

3-1-F

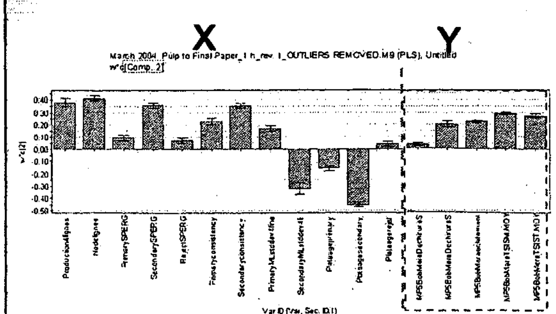


3-1-F

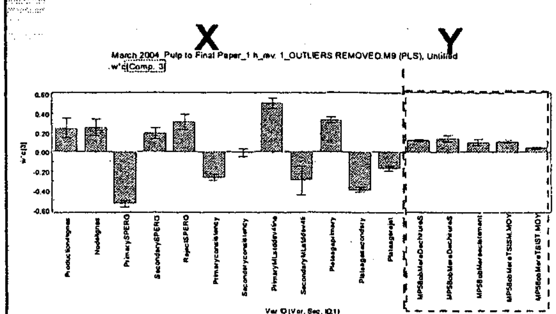
Similar to 3-1-C



3-1-F



3-1-F



3-1-G

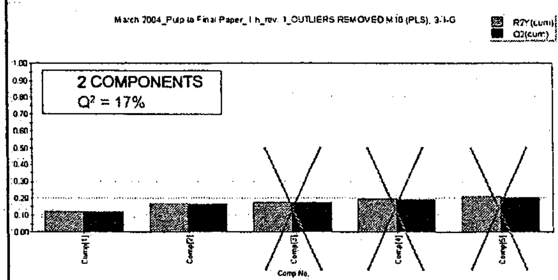
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	$\boxed{\text{3-1-G}}$	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use only hours where Basis Weight = 45 g/m²

Definitive runs/3-1

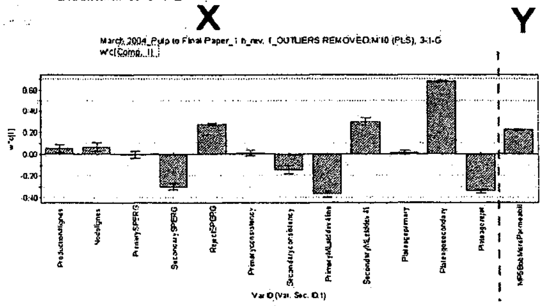
ECOLE POLYTECHNIQUE MONTREAL

3-1-G



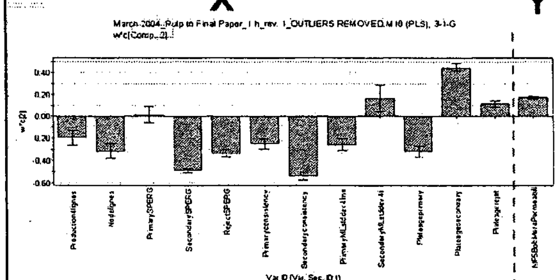
3-1-G

Dissimilar to 3-1-D



3-1-G

Dissimilar to 3-1-D



3-1-H

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	$\boxed{\text{3-1-H}}$
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Definitive runs/3-1

ECOLE POLYTECHNIQUE MONTREAL

3-1-H

- No data for this month

Definitive runs/3-1

ECOLE POLYTECHNIQUE MONTREAL

The « Big Grid »: *a.k.a. Overall Experimental Design*

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	[illegible]	✓	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Definitive runs/4-1

ECOLE POLYTECHNIQUE MONTREAL

4-1-A

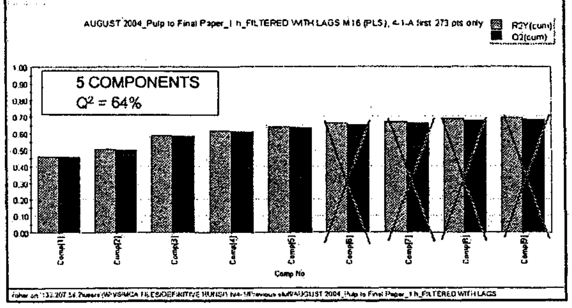
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	[illegible]	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Limited to first 273 datapoints only (PulpExpert problems)

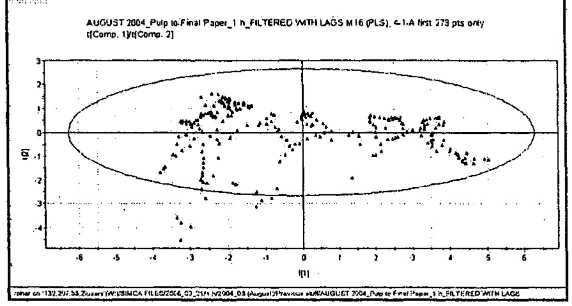
Definitive runs/4-1

ECOLE POLYTECHNIQUE MONTREAL

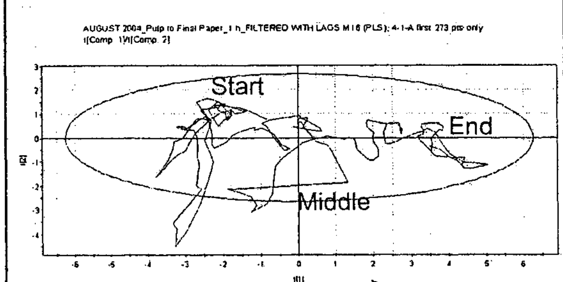
4-1-A



4-1-A



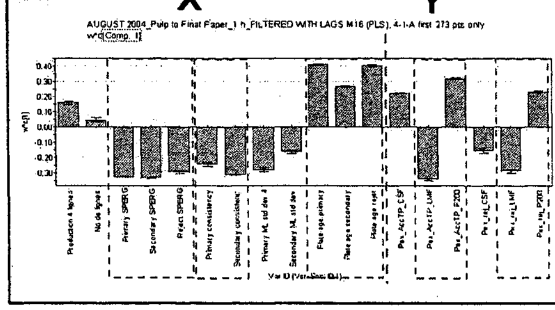
4-1-A



Interprétation: écoulement du temps?

4-1-A

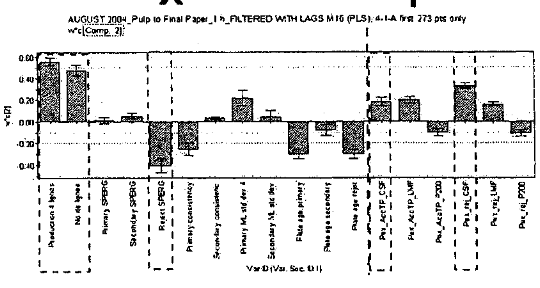
Interprétation: écoulement du temps? Ou bien vieillissement graduel des plaques... **X** **Y**



4-1-A

Interprétation: interaction production/rejets?

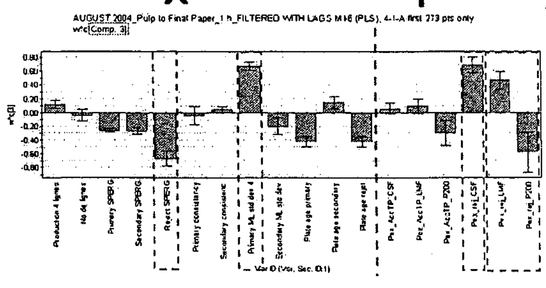
X Y



4-1-A

Interprétation: énergie aux rejets ⇒ CSF et longueur de fibre?

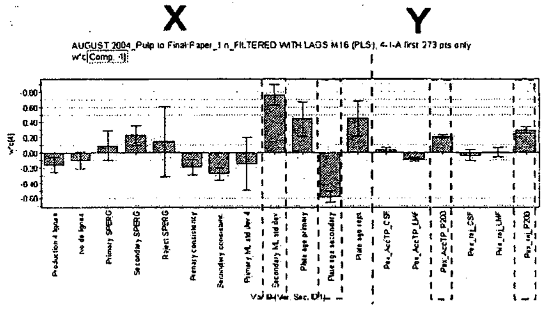
X Y



4-1-A

Interprétation: nouvelles plaques 2° ⇒ fibres moins coupées?

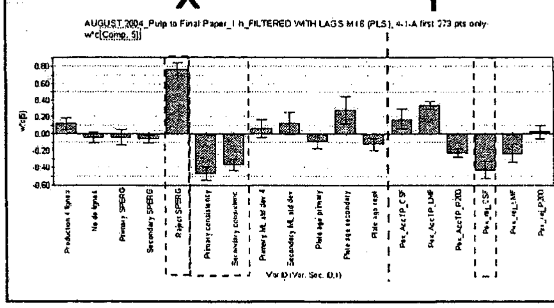
X Y



4-1-A

Interprétation: consistances 1° et 2° ⇒ rejets?

X Y



4-1-B

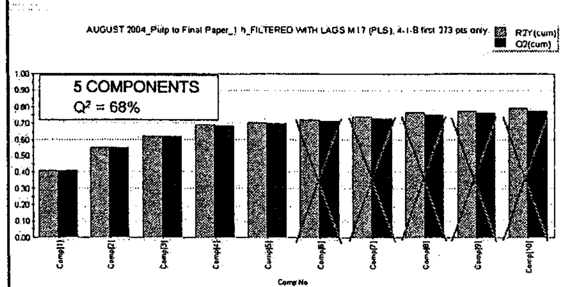
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AllmFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	$\boxed{4-1-B}$	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Limited to first 273 datapoints only (PulpExpert problems)

Definitive runs/4-1

ÉCOLE POLYTECHNIQUE MONTRÉAL

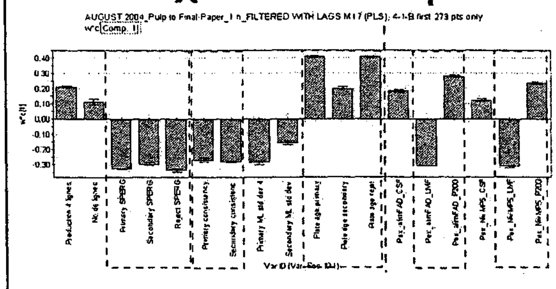
4-1-B



4-1-B

Interprétation: écoulement du temps?

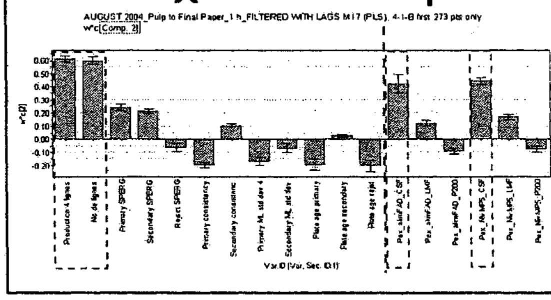
X **Y**



4-1-B

Interprétation: production vs. freeness?

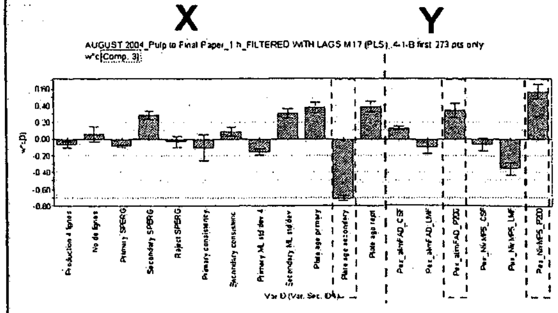
X **Y**



4-1-B

Interprétation: nouvelles plaques 2° ⇒ fibres moins coupées?

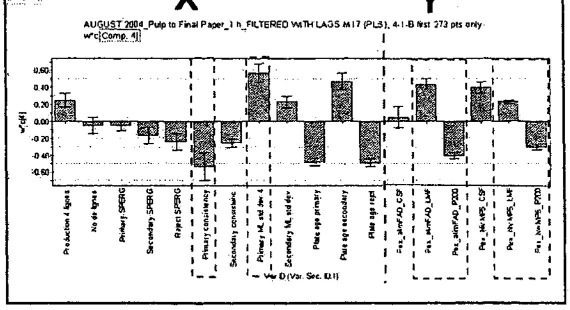
X **Y**



4-1-B

Interprétation: consistance/stabilité au 1° ⇒ fibres moins coupées?

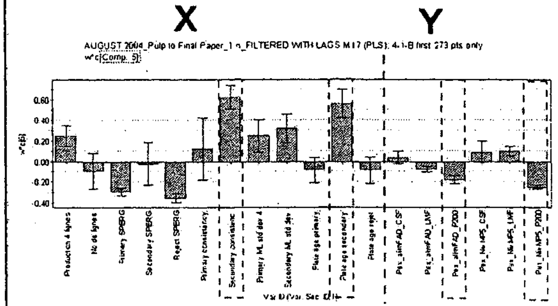
X **Y**



4-1-B

Interprétation: consistance au 2° ⇒ fibres moins coupées?

X **Y**



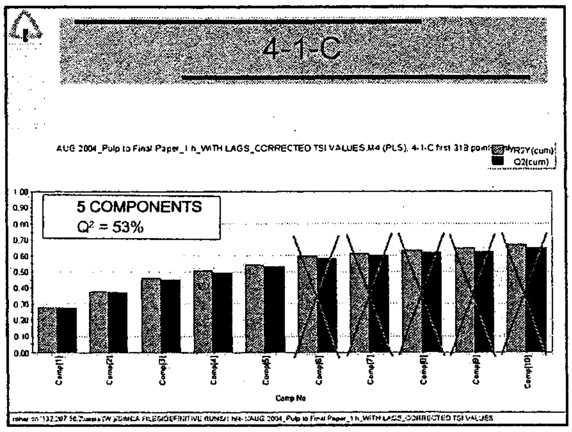
4-1-C

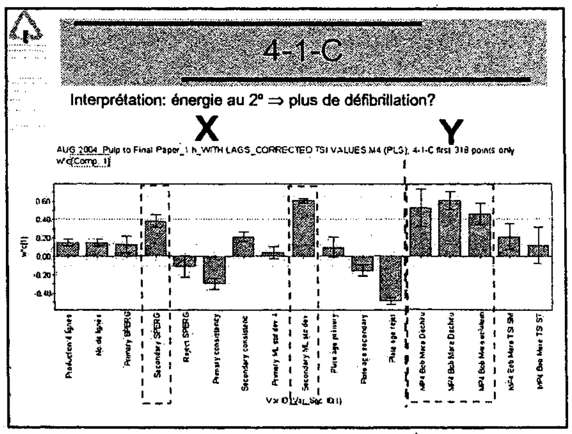
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	$\boxed{\text{4-1-C}}$	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

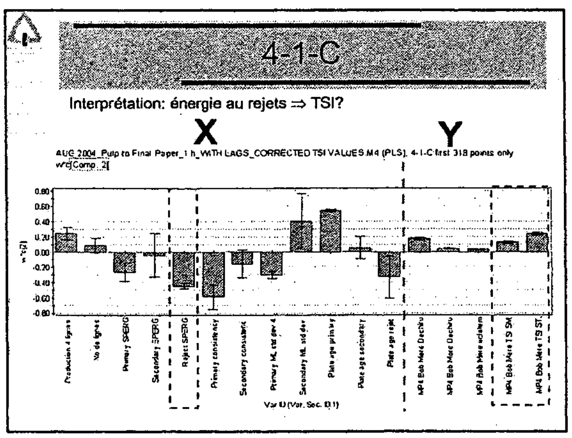
Limited to first 318 datapoints only
(Calibration problems with TSI)

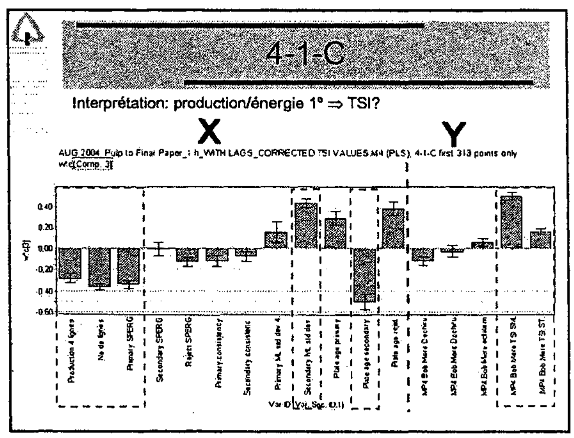
Definitive runs/4-1

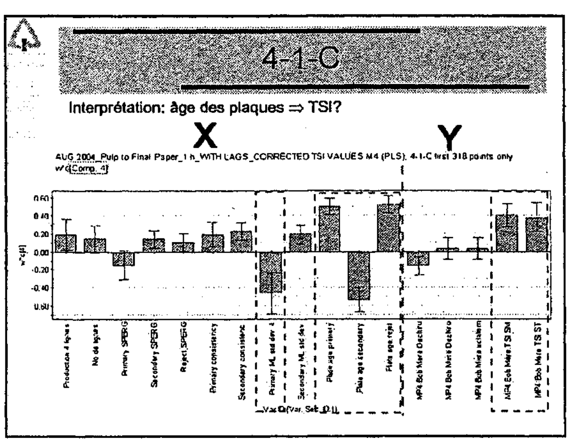
ÉCOLE POLYTECHNIQUE MONTRÉAL

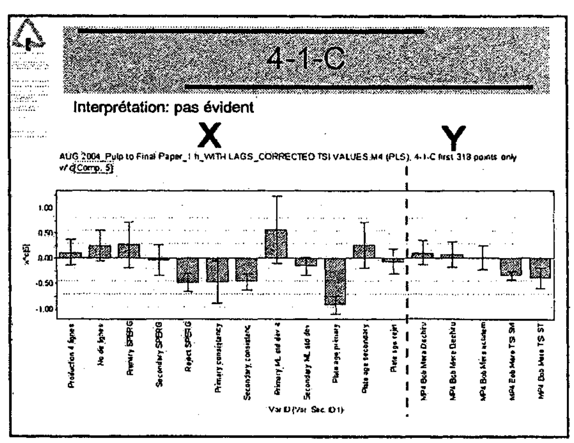

4-1-C
AUG 2004_Pulp to Final Paper_1 h_WITH LAGS_CORRECTED TSI VALUES.M4 (PLS), 4-1-C first 318 points
R2Y(cum)
Q2(cum)
5 COMPONENTS
Q² = 53%
Comp No


4-1-C
Interprétation: énergie au 2° ⇒ plus de défibrillation?
X
Y
AUG 2004_Pulp to Final Paper_1 h_WITH LAGS_CORRECTED TSI VALUES.M4 (PLS), 4-1-C first 318 points only
w*c[Comp. 1]


4-1-C
Interprétation: énergie au rejets ⇒ TSI?
X
Y
AUG 2004_Pulp to Final Paper_1 h_WITH LAGS_CORRECTED TSI VALUES.M4 (PLS), 4-1-C first 318 points only
w*c[Comp. 2]


4-1-C
Interprétation: production/énergie 1° ⇒ TSI?
X
Y
AUG 2004_Pulp to Final Paper_1 h_WITH LAGS_CORRECTED TSI VALUES.M4 (PLS), 4-1-C first 318 points only
w*c[Comp. 3]


4-1-C
Interprétation: âge des plaques ⇒ TSI?
X
Y
AUG 2004_Pulp to Final Paper_1 h_WITH LAGS_CORRECTED TSI VALUES.M4 (PLS), 4-1-C first 318 points only
w*c[Comp. 4]


4-1-C
Interprétation: pas évident
X
Y
AUG 2004_Pulp to Final Paper_1 h_WITH LAGS_CORRECTED TSI VALUES.M4 (PLS), 4-1-C first 318 points only
w*c[Comp. 5]

4-1-D

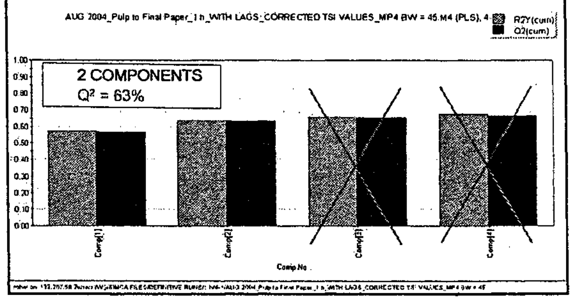
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	$\boxed{4\text{-}1\text{-}D}$	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use only hours where Basis Weight = 45 g/m²

Definitive runs/4-1

ÉCOLE POLYTECHNIQUE MONTRÉAL

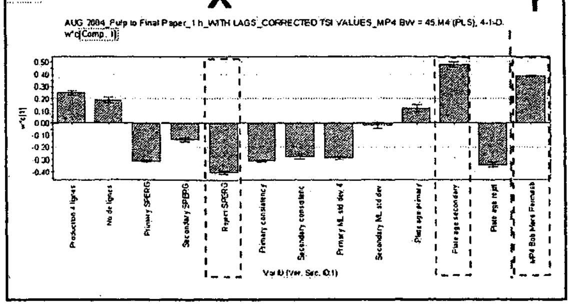
4-1-D



4-1-D

Interprétation: énergie rejets ⇒ perméabilité?

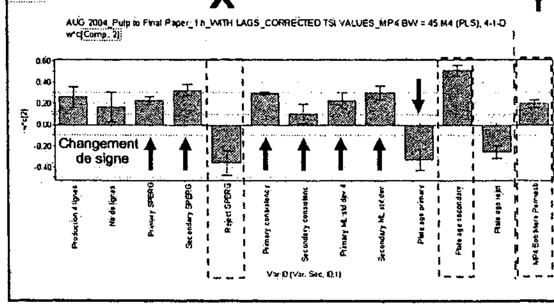
X **Y**



4-1-D

Interprétation: énergie 1°/consistances ⇒ perméabilité?

X **Y**



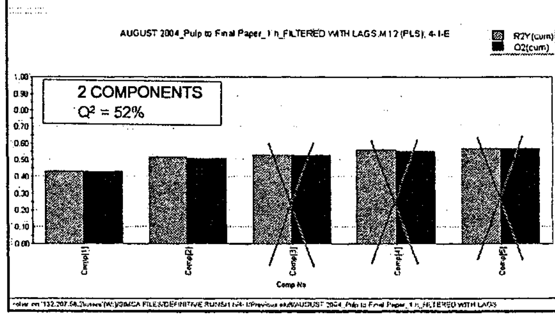
4-1-E

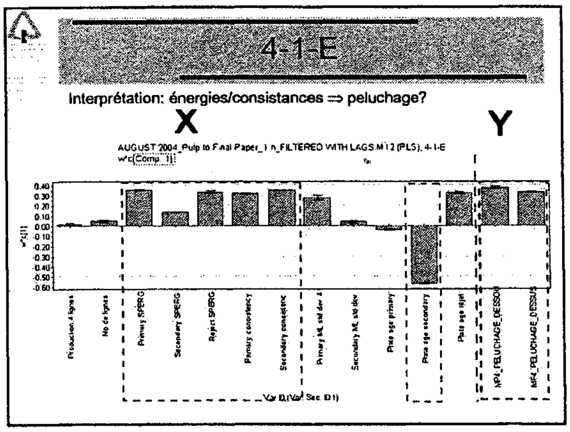
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	$\boxed{4\text{-}1\text{-}E}$	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

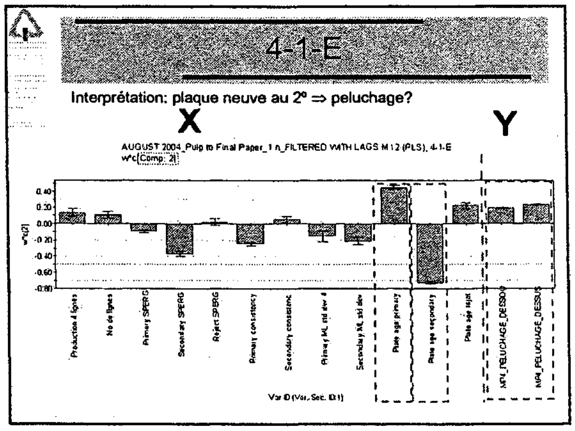
Definitive runs/4-1

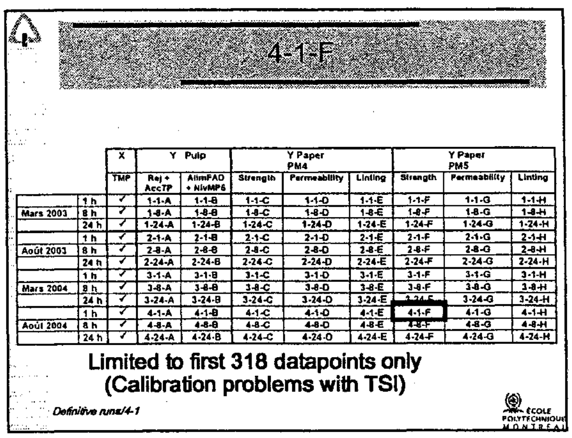
ÉCOLE POLYTECHNIQUE MONTRÉAL

4-1-E

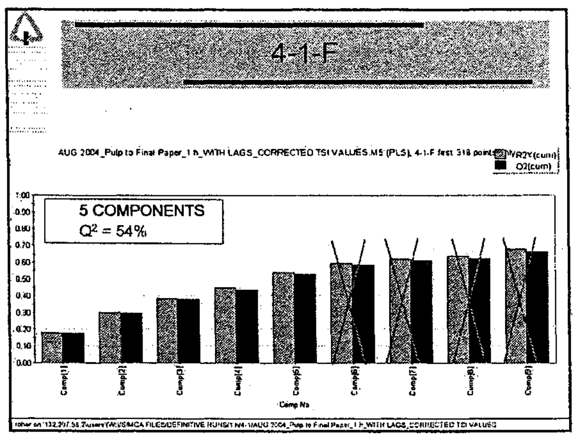


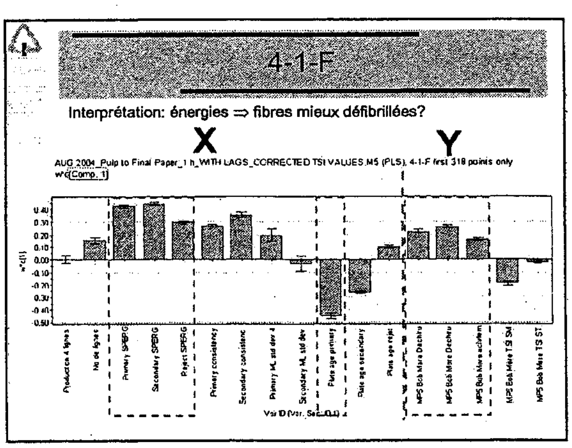


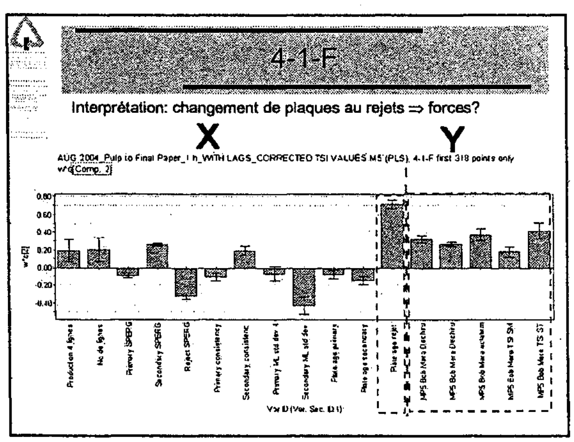


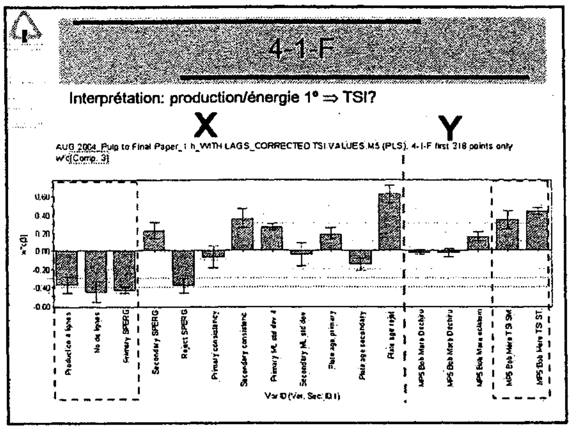


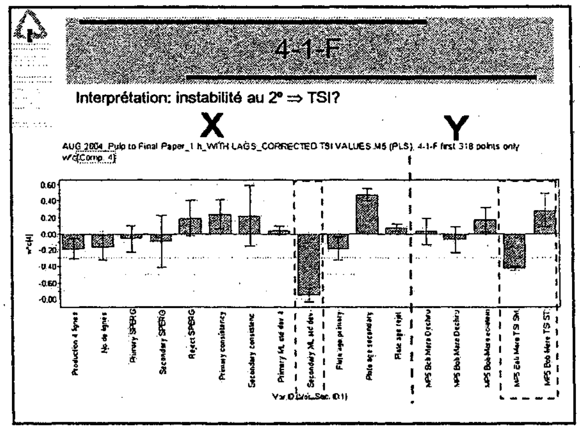
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAO + NivMP6	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

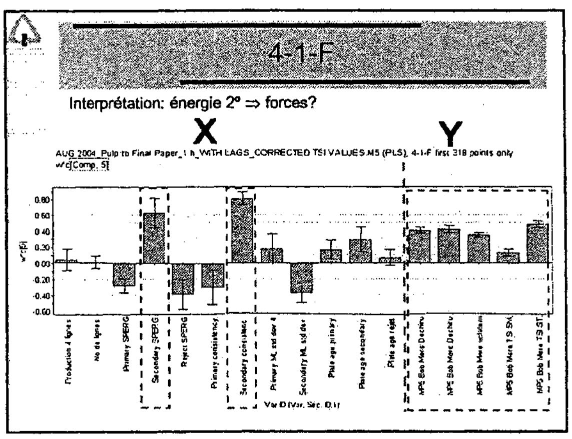












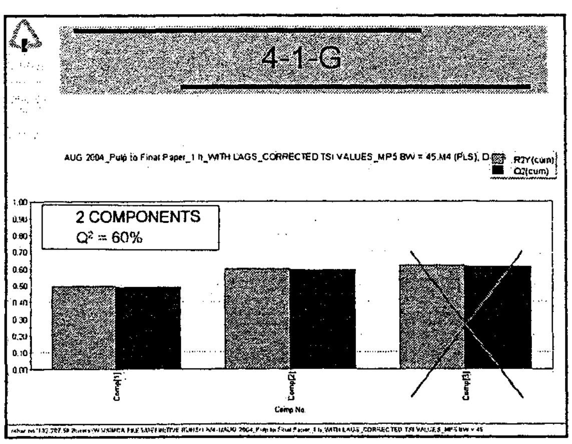
4-1-G

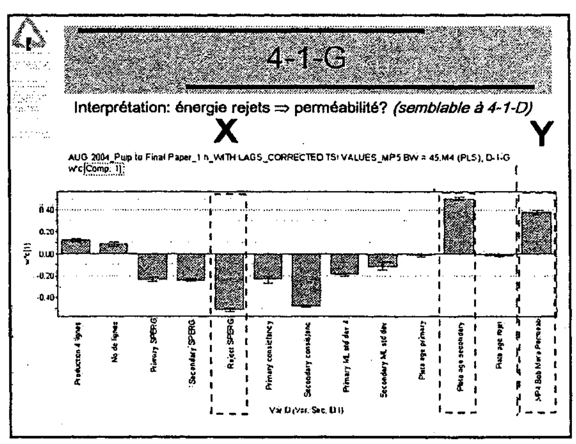
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	[illegible]	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	$\boxed{4\text{-}1\text{-}G}$	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

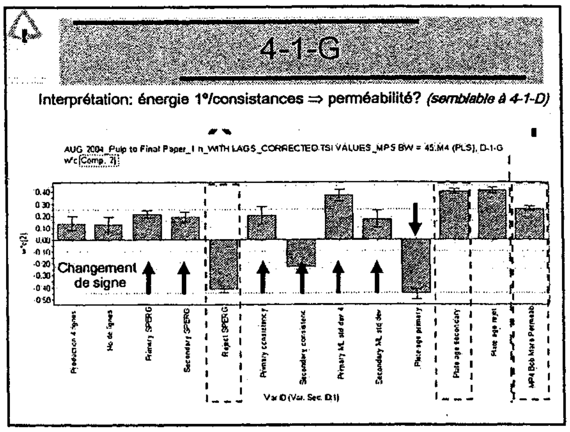
Use only hours where Basis Weight = 45 g/m²

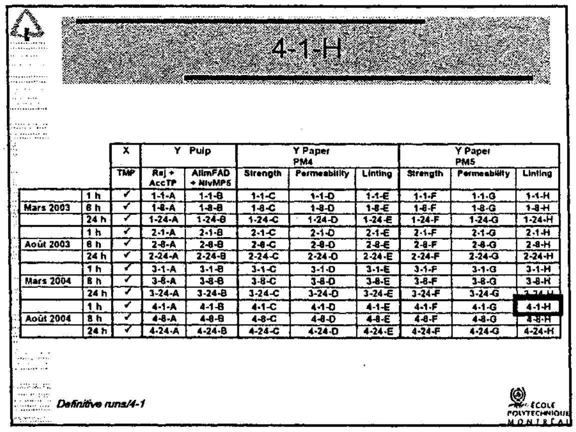
Definitive runs/4-1

ÉCOLE POLYTECHNIQUE MONTRÉAL



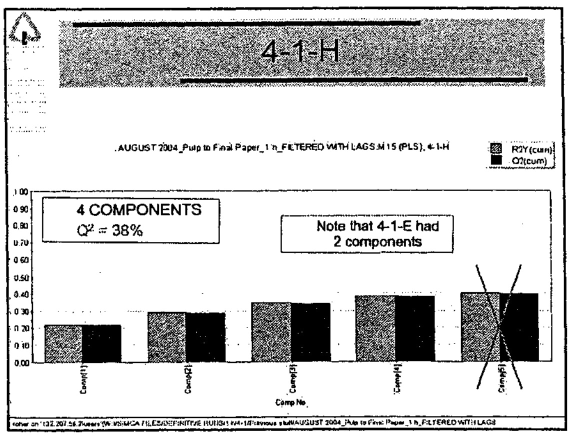


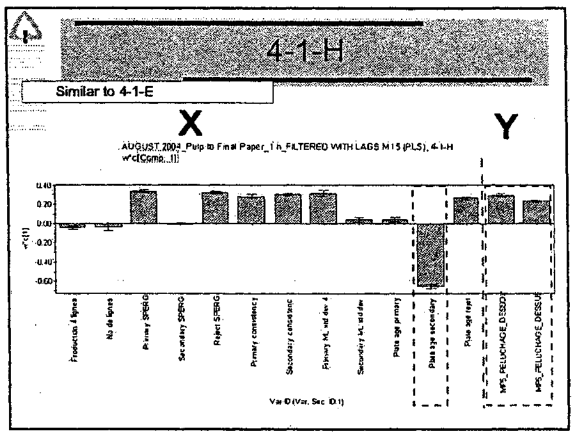


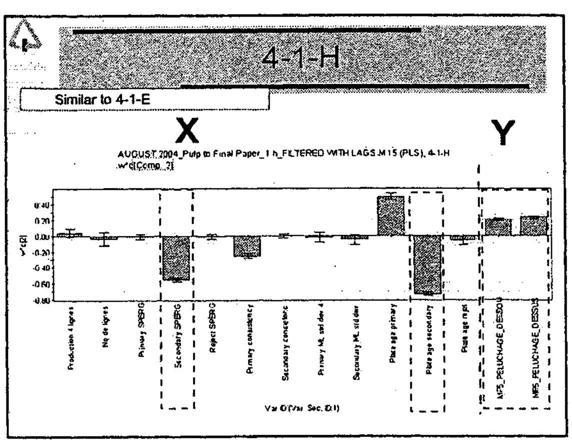


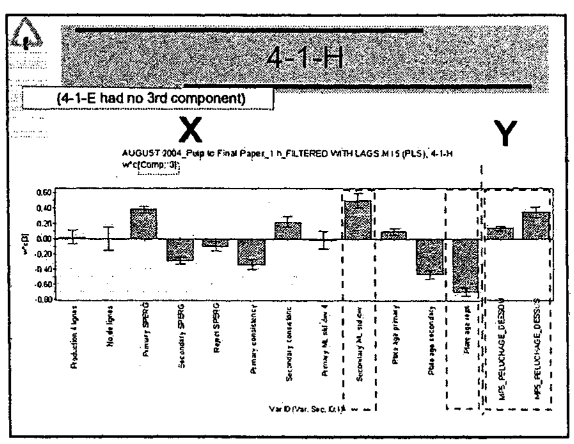
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	[illegible]
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

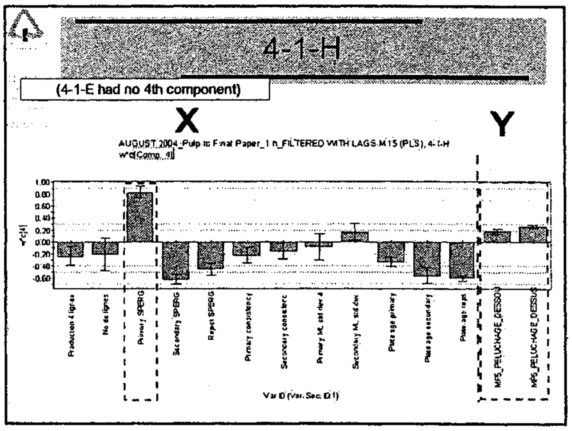
Definitive runs/4-1

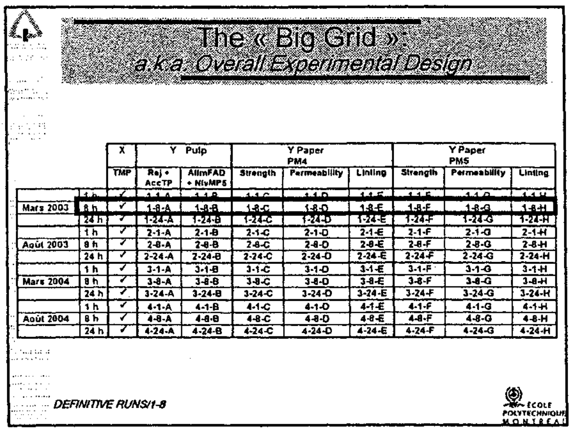




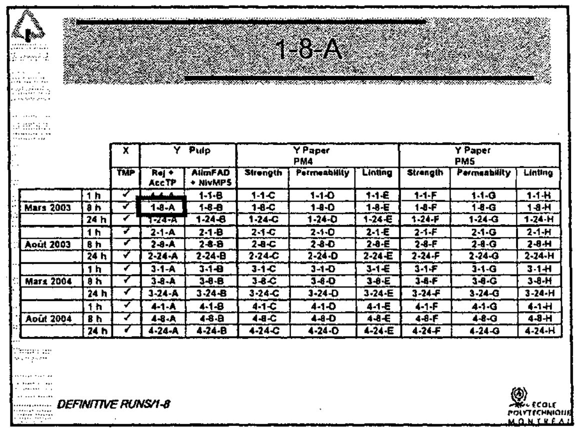




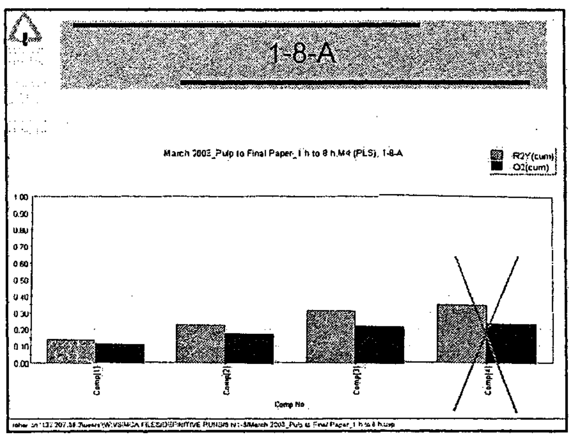

4-1-H
(4-1-E had no 4th component)
X
Y
AUGUST 2004_Pulp to Final Paper_1 h_FILTERED WITH LAGS M15 (PLS), 4-1-H
w*c[Comp. 4]
1.00
0.80
0.60
0.40
0.20
0.00
-0.20
-0.40
-0.60
Production 4 lignes
No de lignes
Primary SPERG
Secondary SPERG
Reject SPERG
Primary consistency
Secondary consistenc
Secondary M, std dev
Passage primary
Passage secondary
MPS_PELUCHAGE_DESSOU
MPS_PELUCHAGE_DESSUS
Var ID (Var. Sec. ID 1)

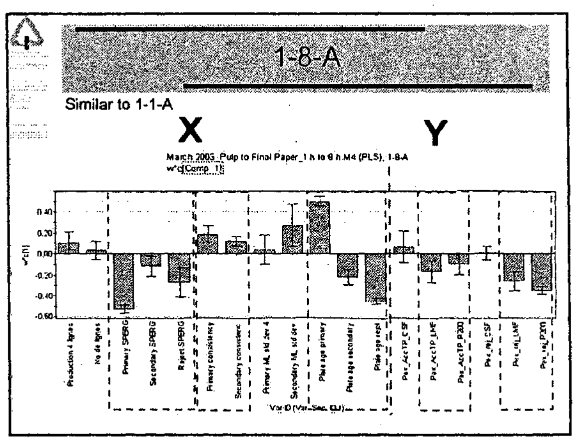


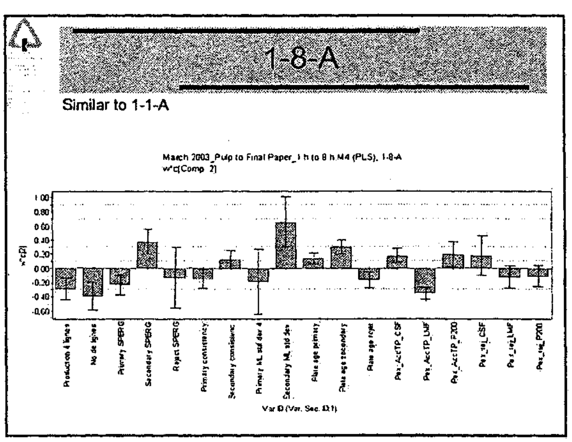
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

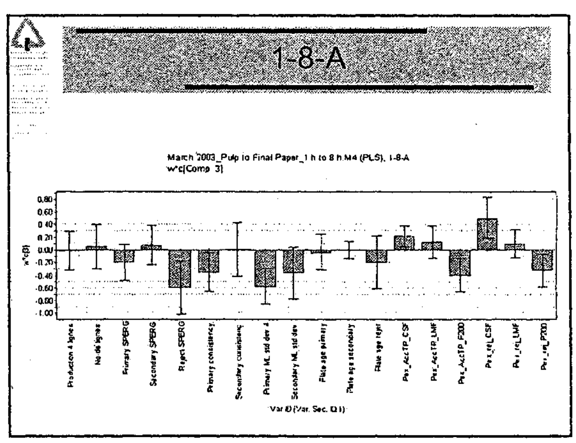


		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H









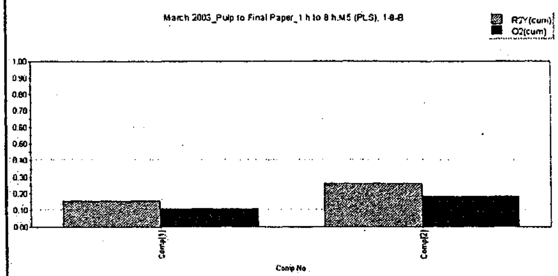
1-8-B

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	$\boxed{1\text{-}8\text{-}B}$	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/1-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

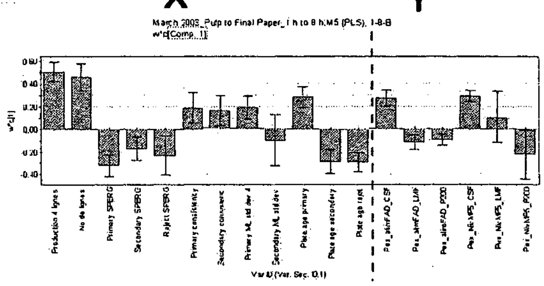
1-8-B



1-8-B

Similar to 1-1-B

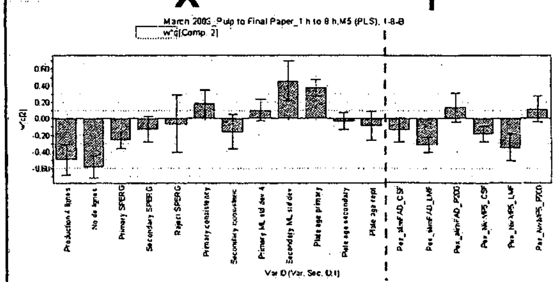
X **Y**



1-8-B

Similar to 1-1-B (upside down)

X **Y**



1-8-C

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	$\boxed{1\text{-}8\text{-}C}$	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/1-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

1-8-C

- Zero components

Whereas 4 components for 1-1-C

DEFINITIVE RUNS/1-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

1-8-D

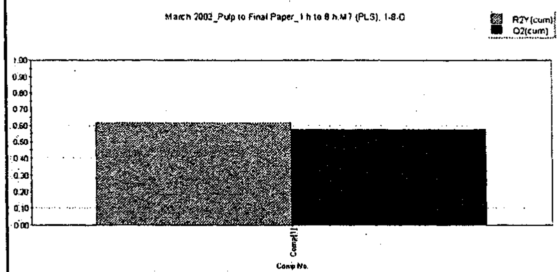
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Just blocks where basis weight = 45 g/m²

DEFINITIVE RUNS/1-8

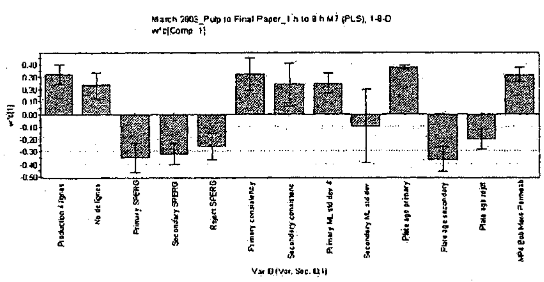
ÉCOLE POLYTECHNIQUE MONTRÉAL

1-8-D



1-8-D

Amalgam of two components in 1-1-D



1-8-E

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/1-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

1-8-E

- No data for this period

DEFINITIVE RUNS/1-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

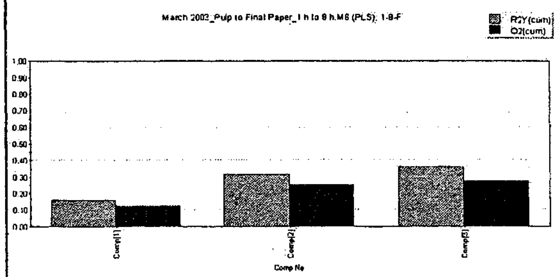
1-8-F

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/1-8

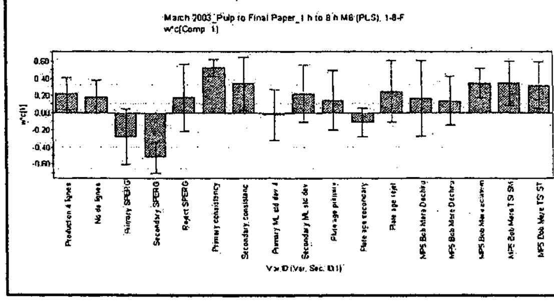
ÉCOLE POLYTECHNIQUE MONTRÉAL

1-8-F

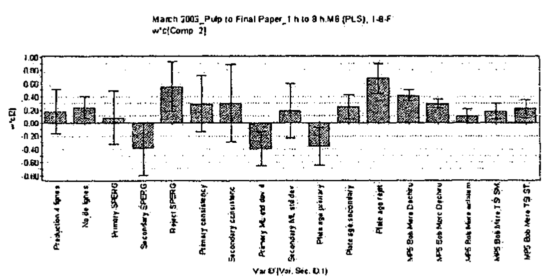


1-8-F

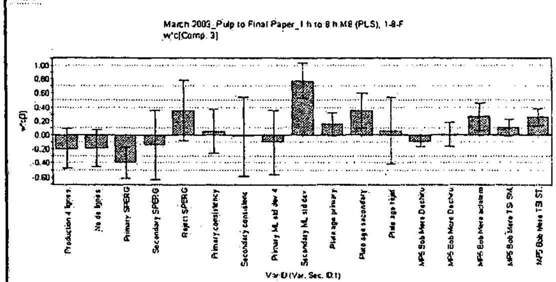
Somewhat similar to 1-1-F



1-8-F



1-8-F



1-8-G

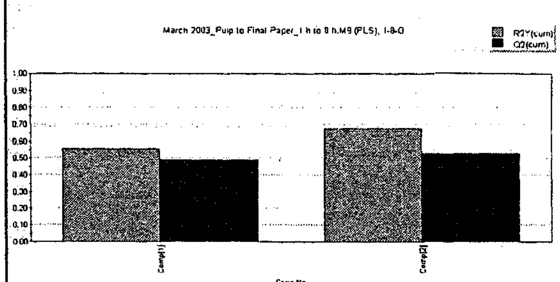
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	$\boxed{\text{1-8-G}}$	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Just blocks where basis weight = 45 g/m²

DEFINITIVE RUNS/1-8

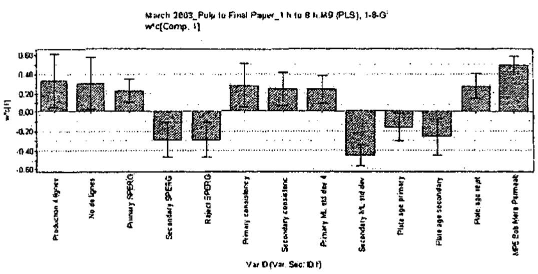
ÉCOLE POLYTECHNIQUE MONTRÉAL

1-8-G

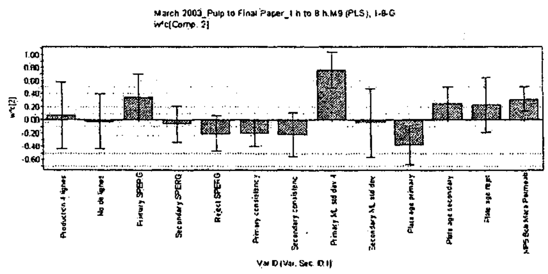


1-8-G

Amalgam of two components in 1-1-G



1-8-G



1-8-H

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAO + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	[illegible]
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	$\boxed{\text{1-8-H}}$
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/1-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

1-8-H

- No data for this period

DEFINITIVE RUNS/1-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

The « Big Grid »: *a.k.a. Overall Experimental Design*

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/2-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

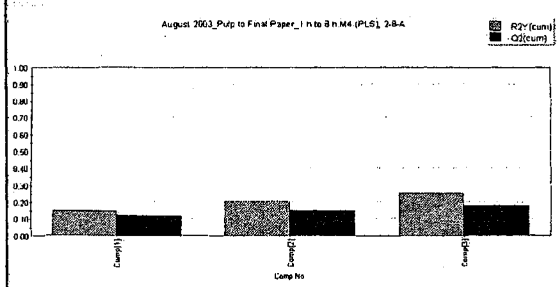
2-8-A

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/2-8

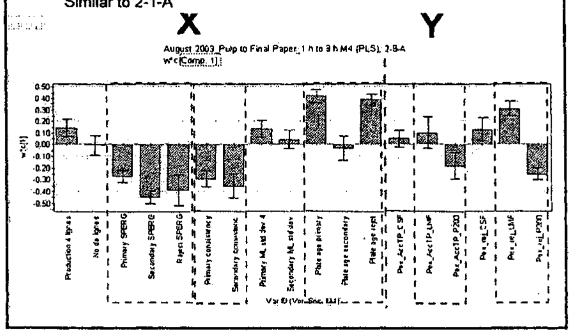
ÉCOLE POLYTECHNIQUE MONTRÉAL

2-8-A

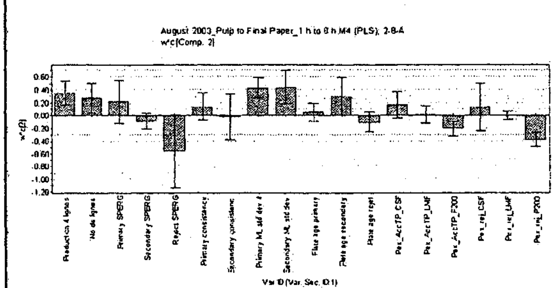


2-8-A

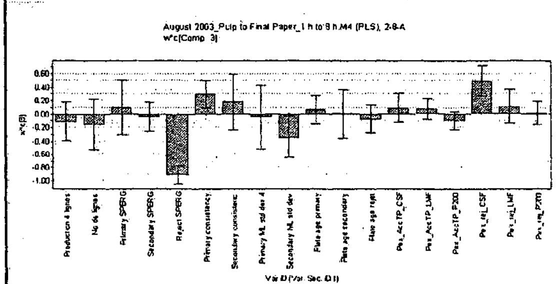
Similar to 2-1-A



2-8-A



2-8-A



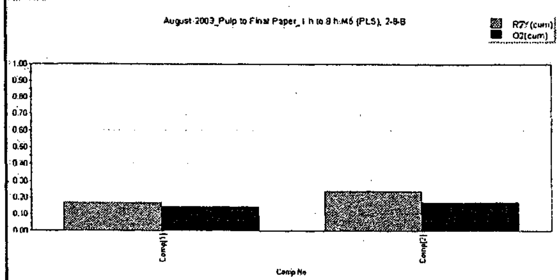
2-8-B

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	$\boxed{\text{2-8-B}}$	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

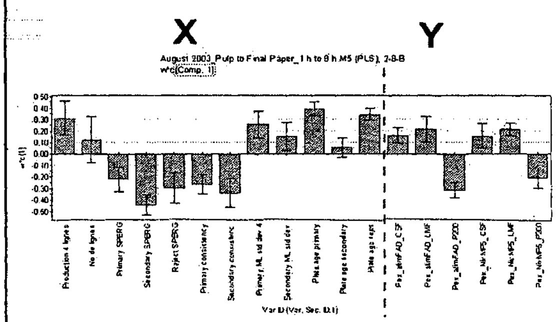
DEFINITIVE RUNS/2-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

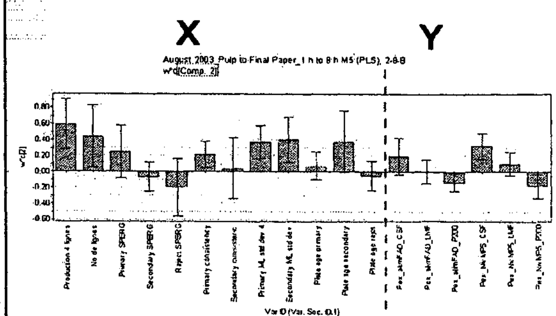
2-8-B



2-8-B



2-8-B



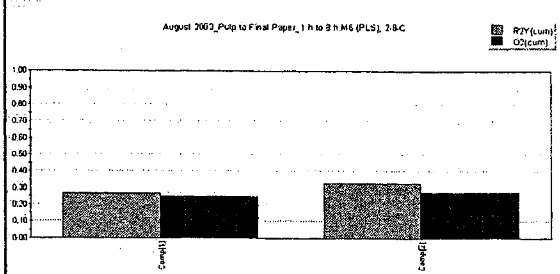
2-8-C

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	$\boxed{\text{2-8-C}}$	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/2-8

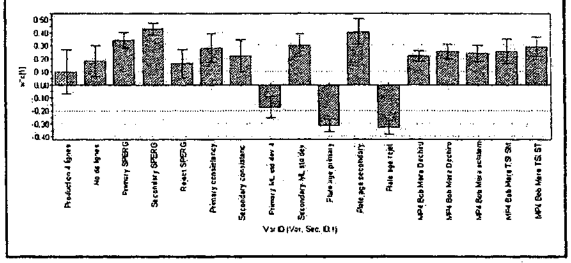
ÉCOLE POLYTECHNIQUE MONTRÉAL

2-8-C

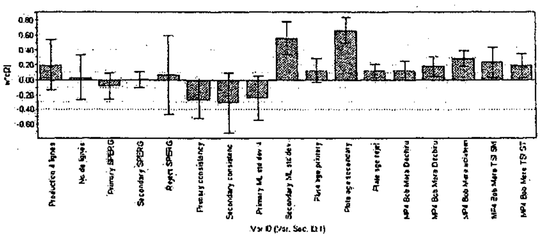


2-8-C

Virtually identical to 2-1-C



2-8-C



2-8-D

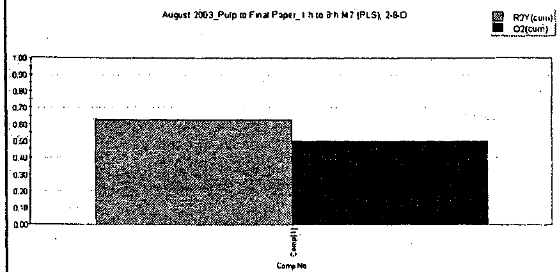
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	$\boxed{\text{2-8-D}}$	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use only blocks where basis weight = 45 g/m^2

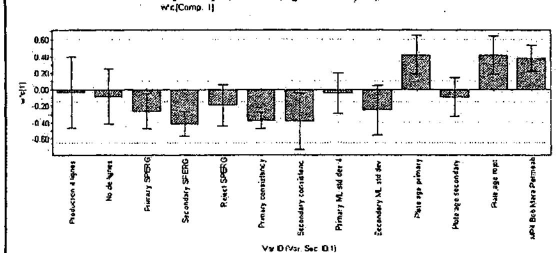
DEFINITIVE RUNS/2-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

2-8-D



2-8-D



2-8-E

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	$\boxed{\text{2-8-E}}$	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/2-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

2-8-E

- No data for this period

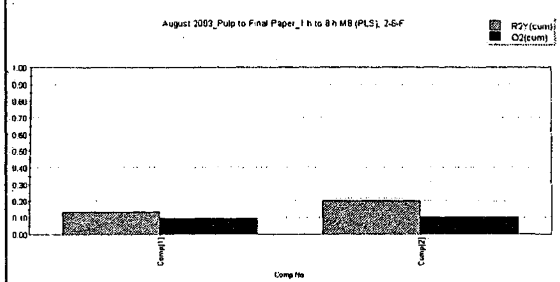
DEFINITIVE RUNS/2-8

2-8-F

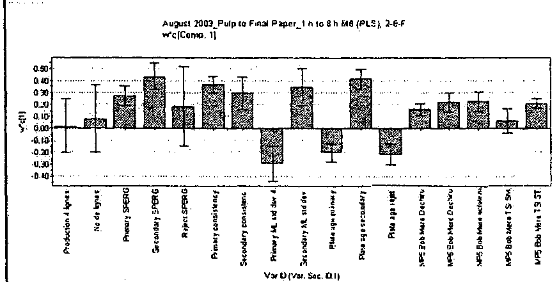
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	$\boxed{\text{2-8-F}}$	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/2-8

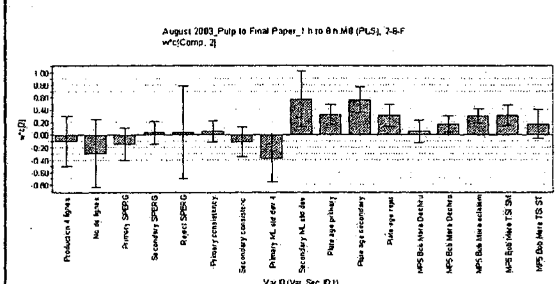
2-8-F



2-8-F



2-8-F



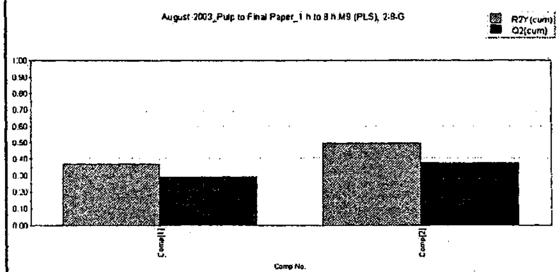
2-8-G

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	$\boxed{\text{2-8-G}}$	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

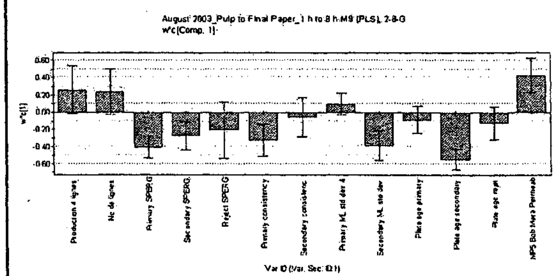
Use only blocks where basis weight = 45 g/m^2

DEFINITIVE RUNS/2-8

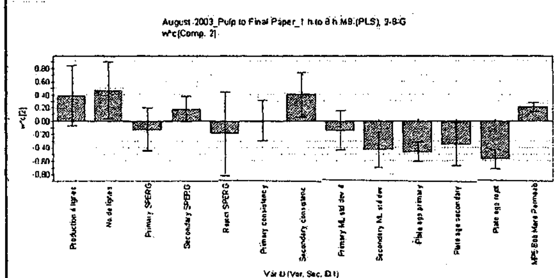
2-8-G



2-8-G



2-8-G



2-8-H

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AllmFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	$\boxed{\text{2-8-H}}$
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS2-8

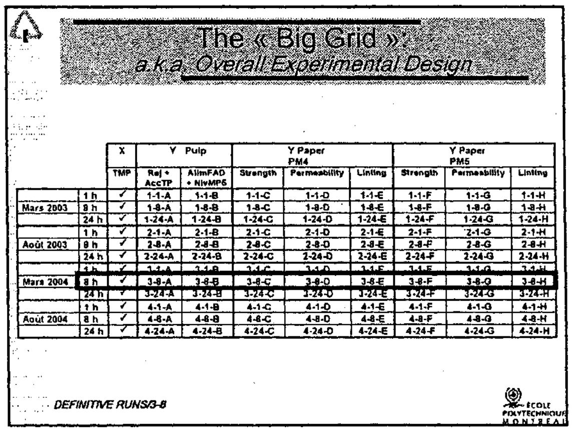
ECOLE POLYTECHNIQUE MONTREAL

2-8-H

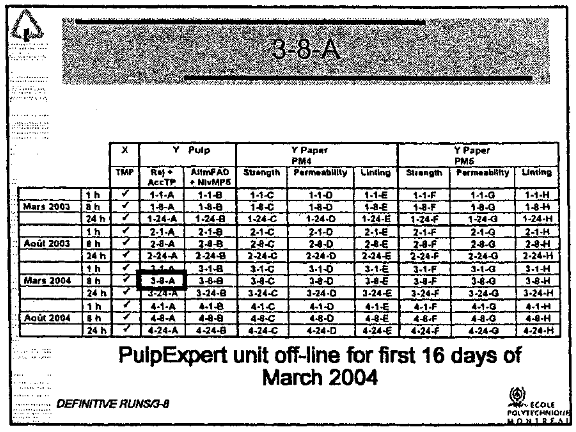
- No data for this period

DEFINITIVE RUNS2-8

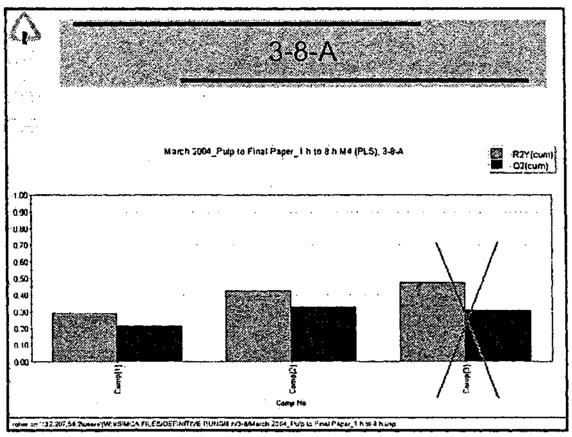
ECOLE POLYTECHNIQUE MONTREAL

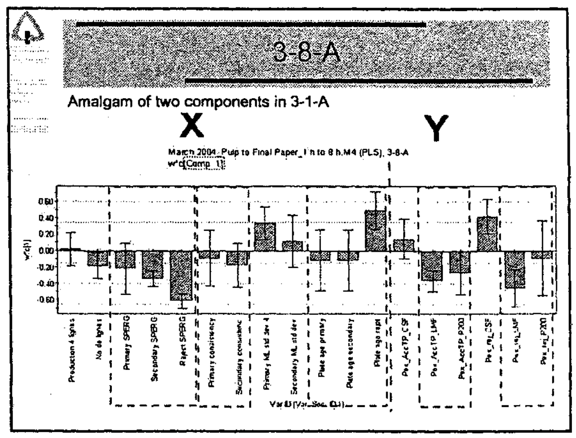


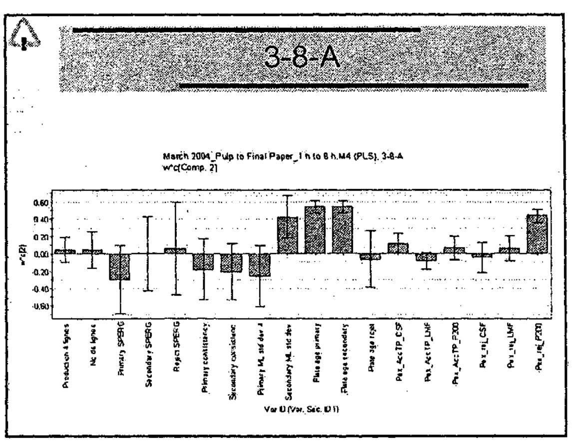
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

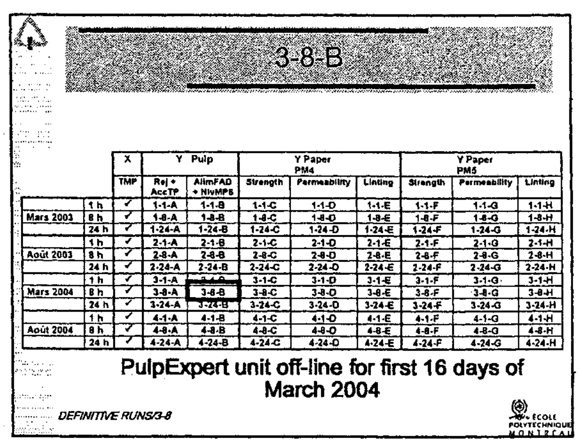


		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H



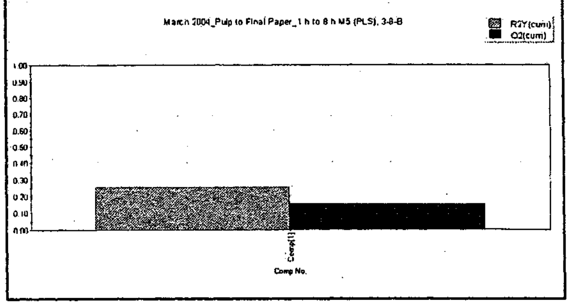




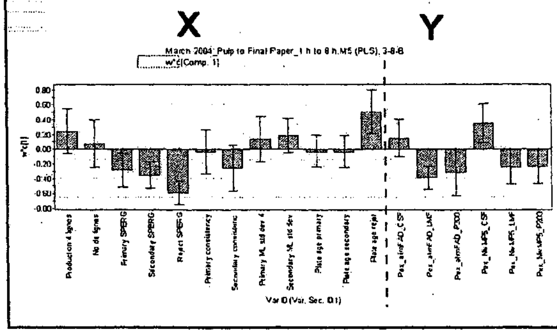


		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

3-8-B



3-8-B



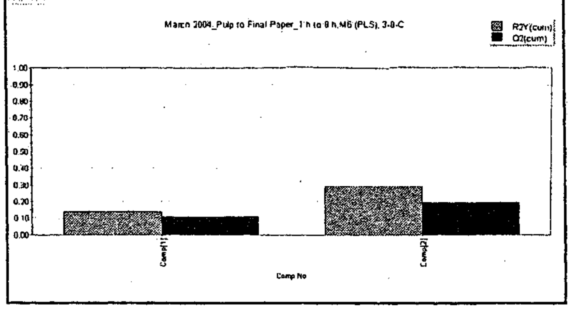
3-8-C

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	$\boxed{3\text{-}8\text{-}C}$	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

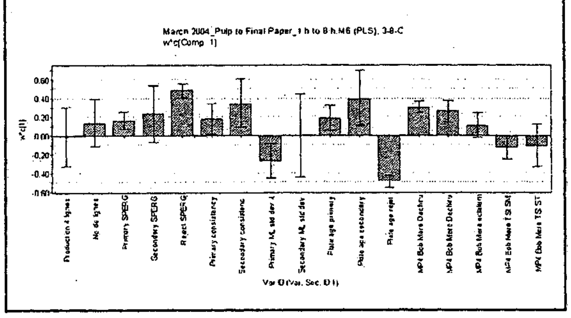
DEFINITIVE RUNS3-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

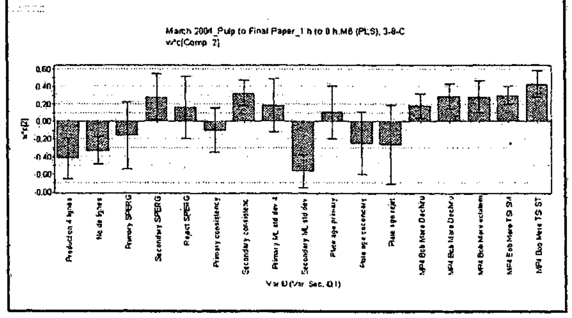
3-8-C



3-8-C



3-8-C



3-8-D

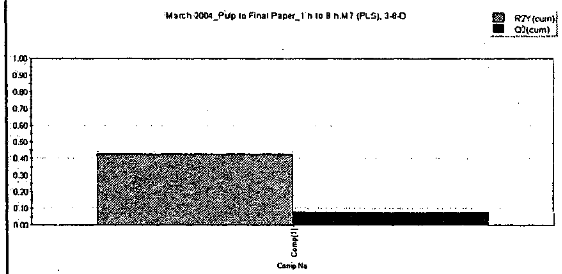
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AllmFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use only blocks where basis weight = 45 g/m²

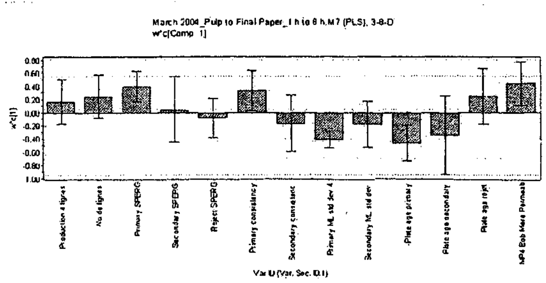
DEFINITIVE RUNS/3-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

3-8-D



3-8-D



3-8-E

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AllmFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/3-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

3-8-E

- No data for this period

DEFINITIVE RUNS/3-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

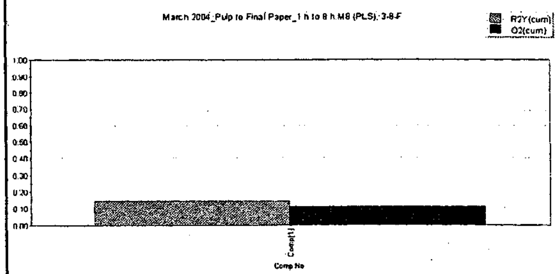
3-8-F

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AllmFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

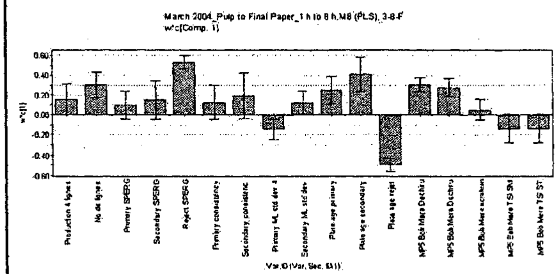
DEFINITIVE RUNS/3-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

3-8-F



3-8-F



3-8-G

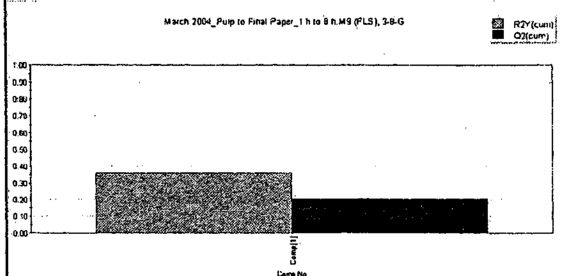
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	$\boxed{\text{3-8-G}}$	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use only blocks where basis weight = 45 g/m²

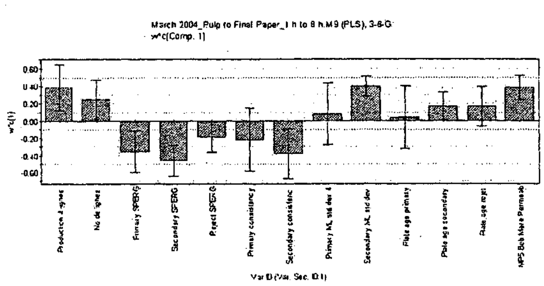
DEFINITIVE RUNS/3-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

3-8-G



3-8-G



3-8-H

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	$\boxed{\text{1-8-H}}$
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/3-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

3-8-H

- No data for this period

DEFINITIVE RUNS/3-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

The « Big Grid »:
a.k.a. Overall Experimental Design

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/4-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

4-8-A

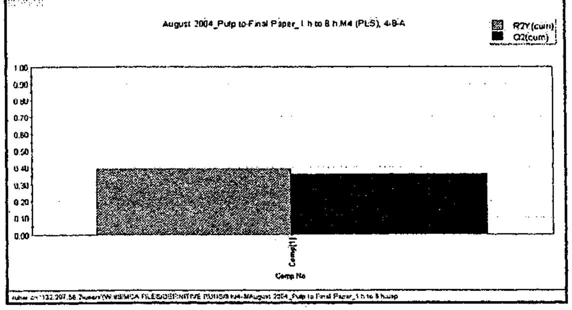
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Limited to first 34 datapoints only
(273 ÷ 8)

DEFINITIVE RUNS/4-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

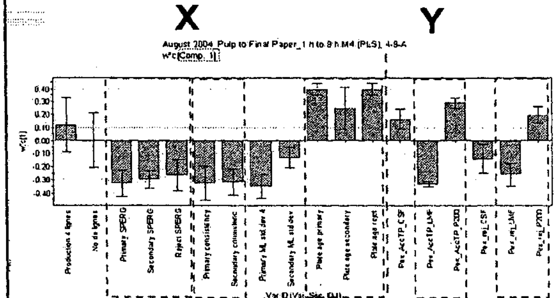
4-8-A



4-8-A

Similar to 4-1-A

X **Y**



4-8-A

- Composantes plus hautes
  - N'existe pas!

DEFINITIVE RUNS/4-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

4-8-B

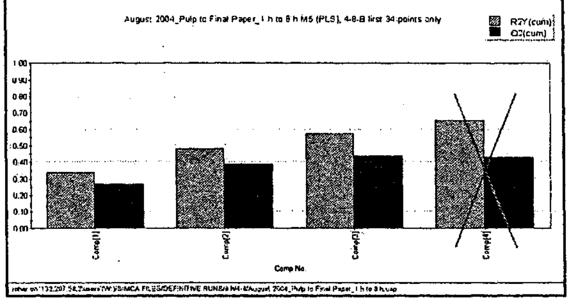
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Limited to first 34 datapoints only
(273 ÷ 8)

DEFINITIVE RUNS/4-8

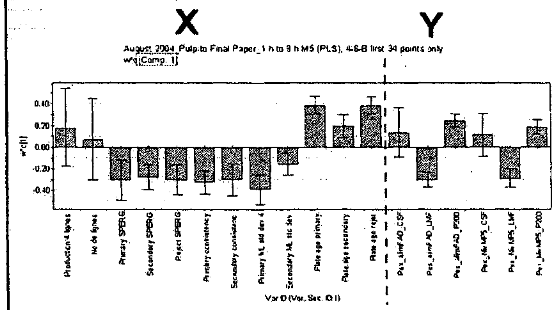
ÉCOLE POLYTECHNIQUE MONTRÉAL

4-8-B



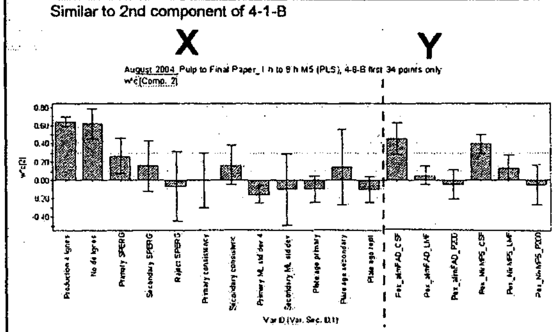
4-8-B

Similar to 1st component of 4-1-B



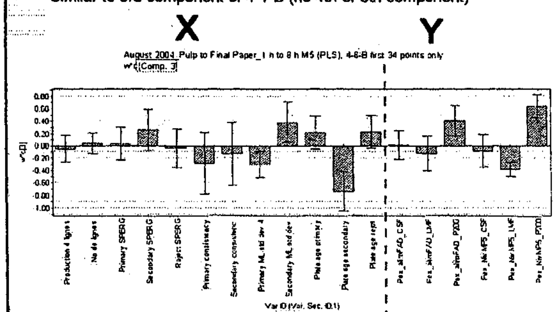
4-8-B

Similar to 2nd component of 4-1-B



4-8-B

Similar to 3rd component of 4-1-B (no 4th or 5th component)



4-8-C

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	$\boxed{\text{4-8-C}}$	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Limited to first 39 datapoints only
(318 ÷ 8)

DEFINITIVE RUNS/4-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

4-8-C

- Zero components

DEFINITIVE RUNS/4-8

ÉCOLE POLYTECHNIQUE MONTRÉAL

4-8-D

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	$\boxed{\text{4-8-D}}$	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

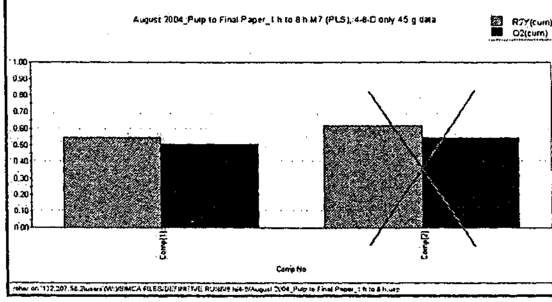
Only use permeability data for periods when Basis Weight = 45 g/m^2 (rest deleted)

DEFINITIVE RUNS/4-8

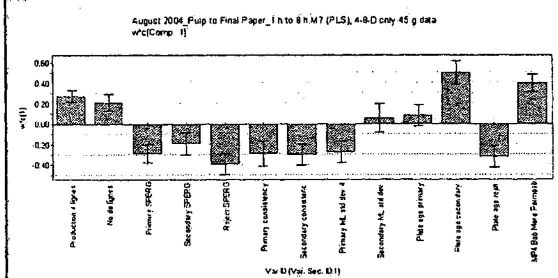
ÉCOLE POLYTECHNIQUE MONTRÉAL

4-8-D

Similar to 1st component of 4-1-D



4-8-D



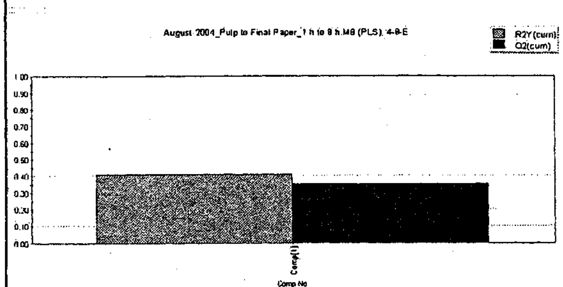
4-8-E

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	$\boxed{\text{4-8-E}}$	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/4-8

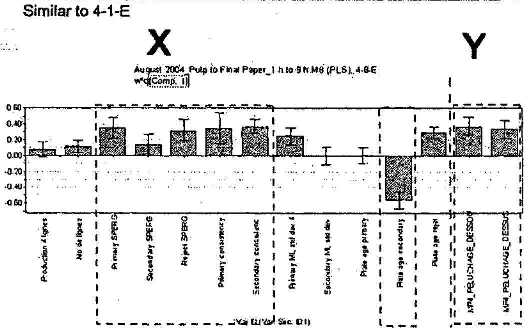
ÉCOLE POLYTECHNIQUE MONTRÉAL

4-8-E



4-8-E

Similar to 4-1-E



4-8-F

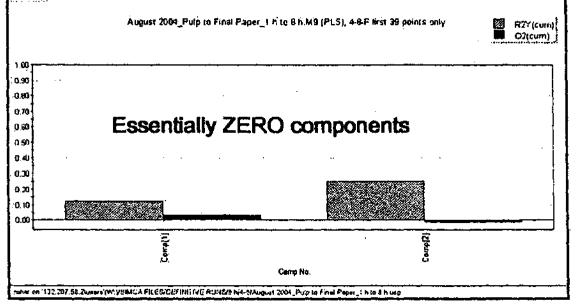
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAO + NivMP6	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	$\boxed{4-8-F}$	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Limited to first 39 datapoints only (318 + 8)

DEFINITIVE RUNS/4-8

ECOLE POLYTECHNIQUE MONTREAL

4-8-F



4-8-G

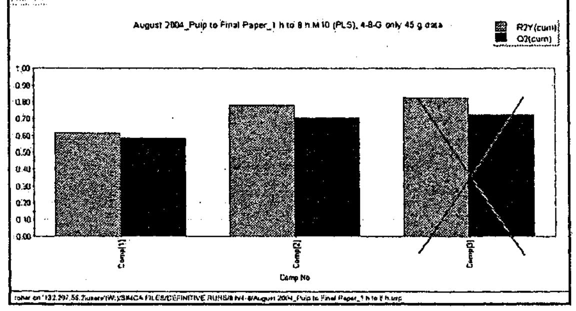
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAO + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	$\boxed{4-8-G}$	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use all periods, despite basis weight fluctuations

DEFINITIVE RUNS/4-8

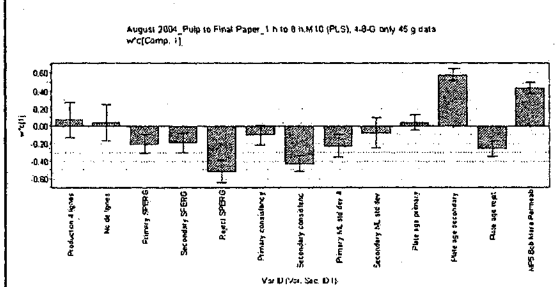
ECOLE POLYTECHNIQUE MONTREAL

4-8-G



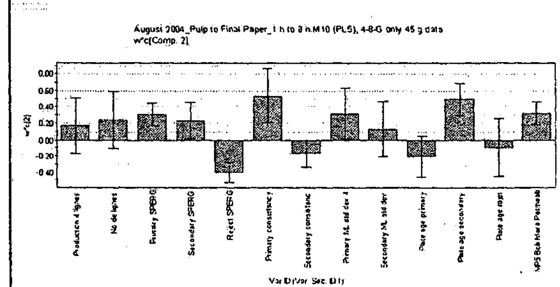
4-8-G

Similar to 1st component of 4-1-G



4-8-G

Similar to 2nd component of 4-1-G



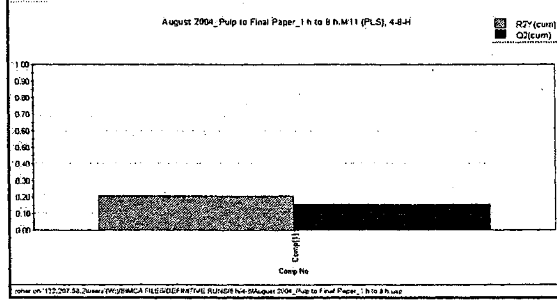
4-8-H

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	$\boxed{4\text{-}8\text{-}H}$
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/4-8

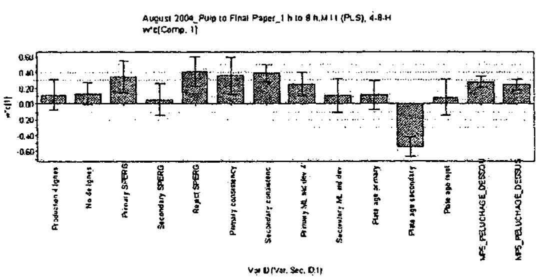
ÉCOLE POLYTECHNIQUE MONTRÉAL

4-8-H



4-8-H

Similar to 1st component of 4-1-H (no 2nd, 3rd or 4th component)



The « Big Grid »: *a.k.a. Overall Experimental Design*

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP6	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/1-24

ÉCOLE POLYTECHNIQUE MONTRÉAL

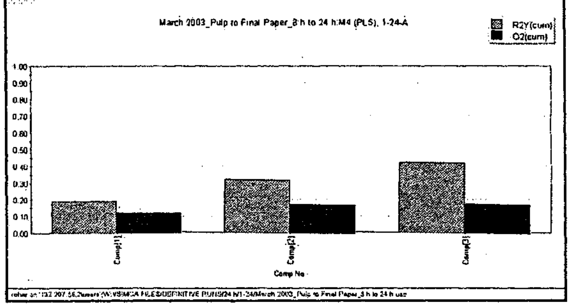
1-24-A

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP6	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/1-24

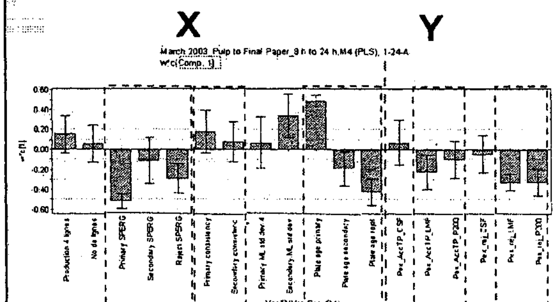
ÉCOLE POLYTECHNIQUE MONTRÉAL

1-24-A

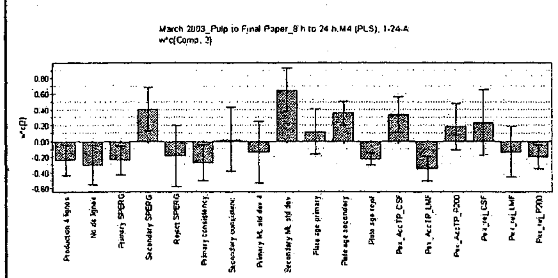


1-24-A

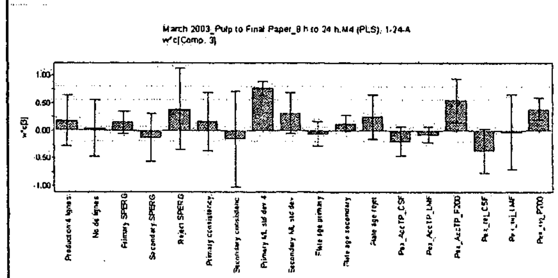
Similar to 1-1-A



1-24-A



1-24-A



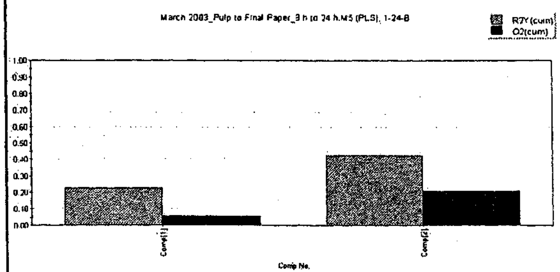
1-24-B

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/1-24

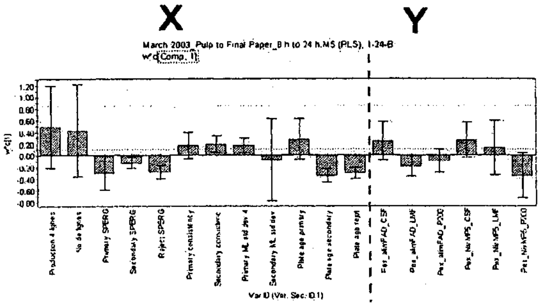
ÉCOLE POLYTECHNIQUE MONTRÉAL

1-24-B

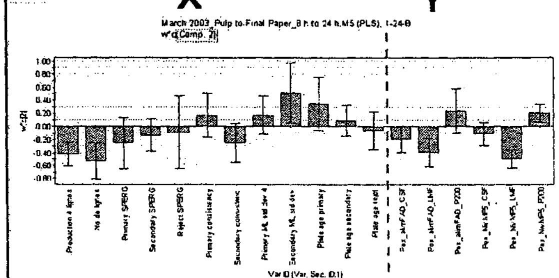


1-24-B

Similar to 1-1-B



1-24-B



1-24-C

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/1-24

ÉCOLE POLYTECHNIQUE MONTRÉAL

1-24-C

- Zero components

Like 1-1-C

DEFINITIVE RUNS/1-24

ÉCOLE POLYTECHNIQUE MONTRÉAL

1-24-D

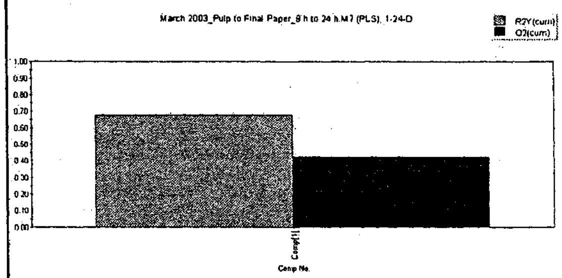
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	$\boxed{\text{1-24-D}}$	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use only blocks where basis weight = 45 g/m²

DEFINITIVE RUNS/1-24

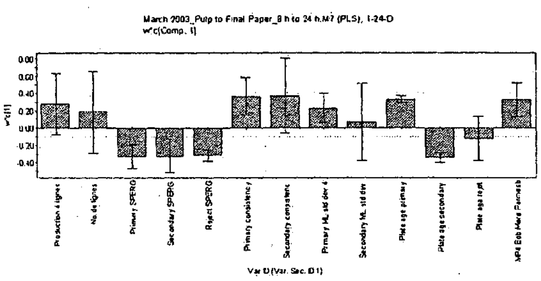
ÉCOLE POLYTECHNIQUE MONTRÉAL

1-24-D



1-24-D

Similar to 1-8-D



1-24-E

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	$\boxed{\text{1-24-E}}$	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/1-24

ÉCOLE POLYTECHNIQUE MONTRÉAL

1-24-E

- No data for this period

DEFINITIVE RUNS/1-24

ÉCOLE POLYTECHNIQUE MONTRÉAL

1-24-F

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	$\boxed{\text{1-24-F}}$	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/1-24

ÉCOLE POLYTECHNIQUE MONTRÉAL

1-24-F

- Zero components

Whereas 3 components for 1-8-F

DEFINITIVE RUNS/1-24

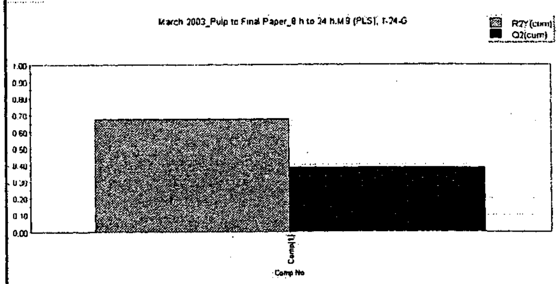
1-24-G

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use only blocks where basis weight = 45 g/m²

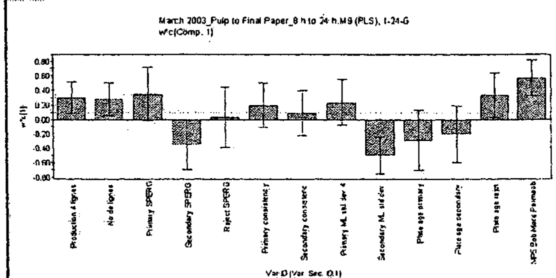
DEFINITIVE RUNS/1-24

1-24-G



1-24-G

Similar to 1-1-G



1-24-H

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/1-24

1-24-H

- No data for this period

DEFINITIVE RUNS/1-24

The « Big Grid »:
a.k.a. Overall Experimental Design

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAO + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/2-24

ÉCOLE POLYTECHNIQUE MONTRÉAL

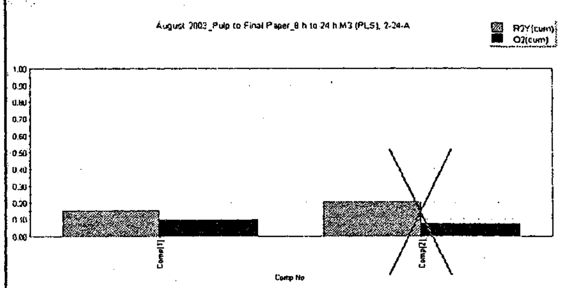
2-24-A

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAO + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

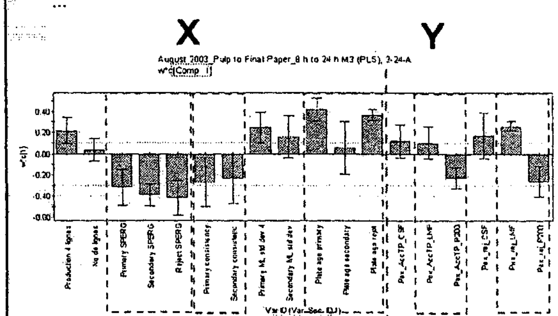
DEFINITIVE RUNS/2-24

ÉCOLE POLYTECHNIQUE MONTRÉAL

2-24-A



2-24-A



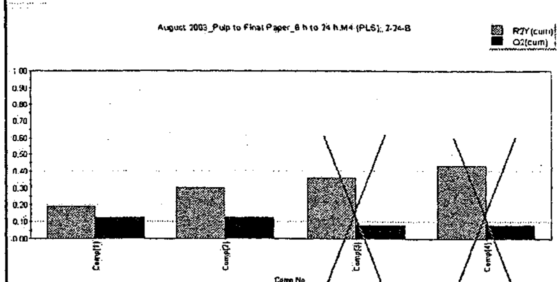
2-24-B

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAO + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/2-24

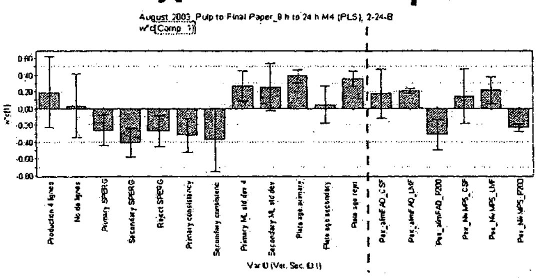
ÉCOLE POLYTECHNIQUE MONTRÉAL

2-24-B



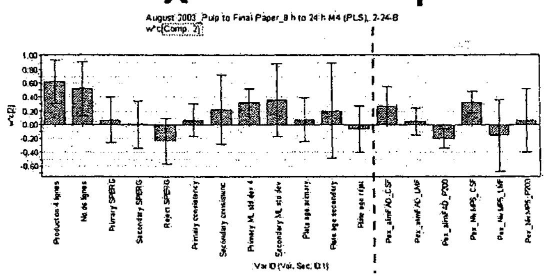
2-24-B

X Y



2-24-B

X Y



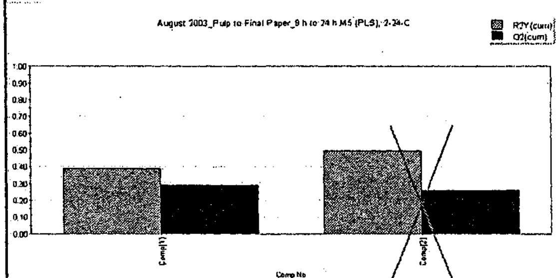
2-24-C

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	**2-24-C**	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

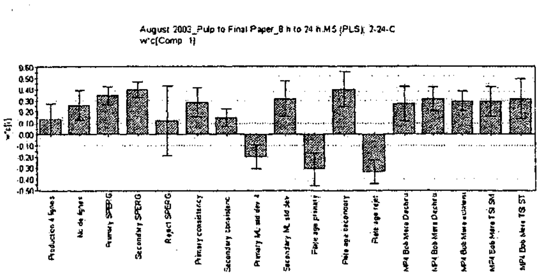
DEFINITIVE RUNS2-24

ECOLE POLYTECHNIQUE MONTREAL

2-24-C



2-24-C



2-24-D

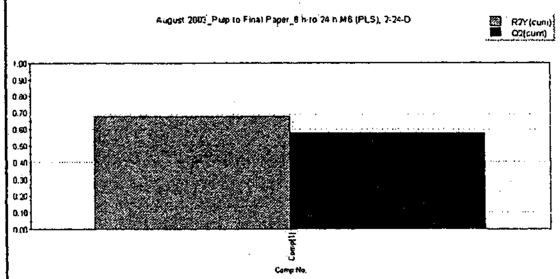
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	**2-24-D**	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use only blocks where basis weight = 45 g/m^2

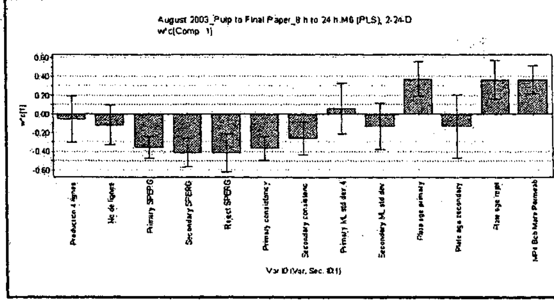
DEFINITIVE RUNS2-24

ECOLE POLYTECHNIQUE MONTREAL

2-24-D



2-24-D



2-24-E

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	$\boxed{\text{2-24-E}}$	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/2-24

ECOLE POLYTECHNIQUE MONTREAL

2-24-E

- No data for this period

DEFINITIVE RUNS/2-24

ECOLE POLYTECHNIQUE MONTREAL

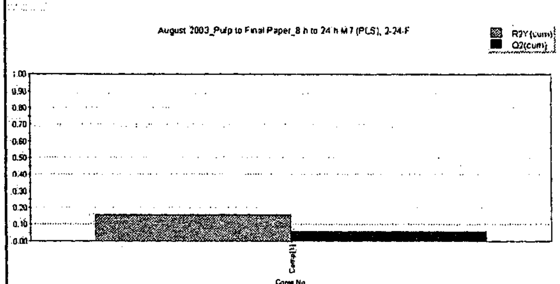
2-24-F

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	$\boxed{\text{2-24-F}}$	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

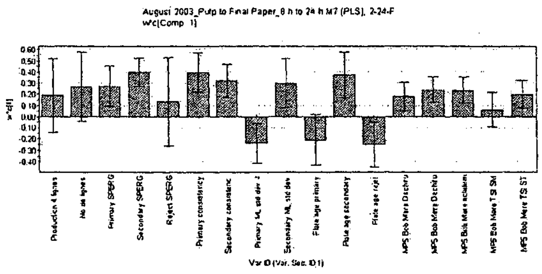
DEFINITIVE RUNS/2-24

ECOLE POLYTECHNIQUE MONTREAL

2-24-F



2-24-F



2-24-G

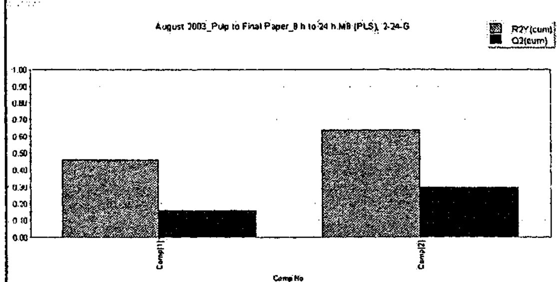
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	$\boxed{\text{2-24-G}}$	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use only blocks where basis weight = 45 g/m^2

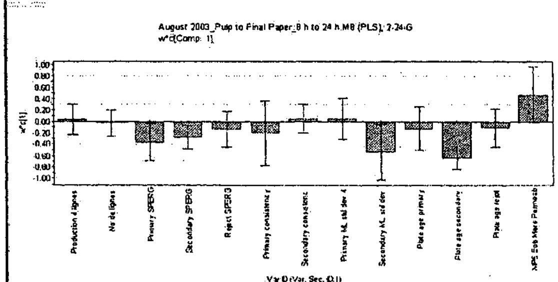
DEFINITIVE RUNS/2-24

ECOLE POLYTECHNIQUE MONTRÉAL

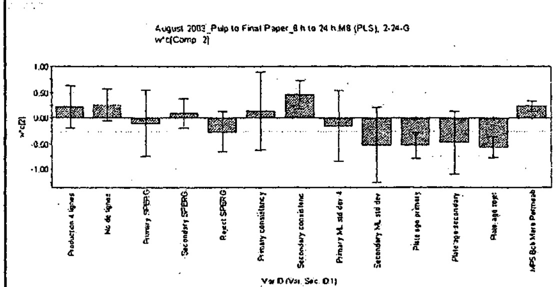
2-24-G



2-24-G



2-24-G



2-24-H

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	$\boxed{\text{2-24-H}}$
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/2-24

ECOLE POLYTECHNIQUE MONTRÉAL

2-24-H

- No data for this period

The « Big Grid »: a.k.a. Overall Experimental Design

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/3-24

ECOLE POLYTECHNIQUE MONTREAL

3-24-A

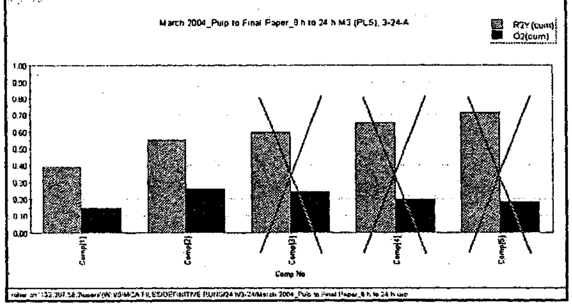
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	[illegible]	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

PulpExpert offline for first 16 days of March 2004

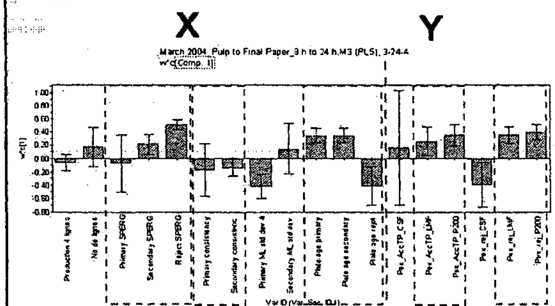
DEFINITIVE RUNS/3-24

ECOLE POLYTECHNIQUE MONTREAL

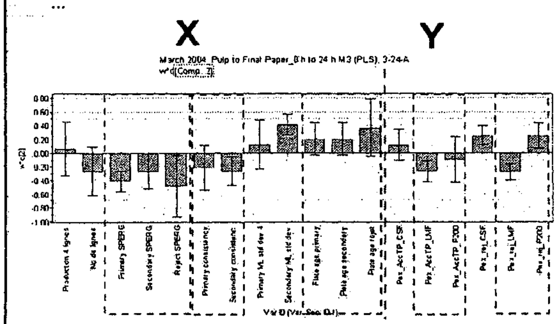
3-24-A



3-24-A



3-24-A



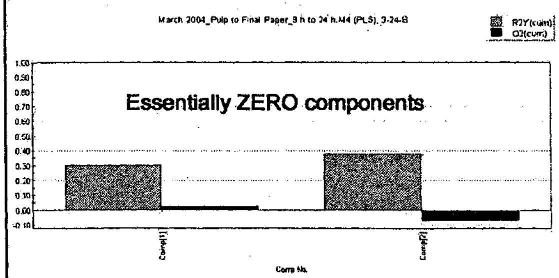
3-24-B

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	[illegible]	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/3-24

ECOLE POLYTECHNIQUE MONTREAL

3-24-B



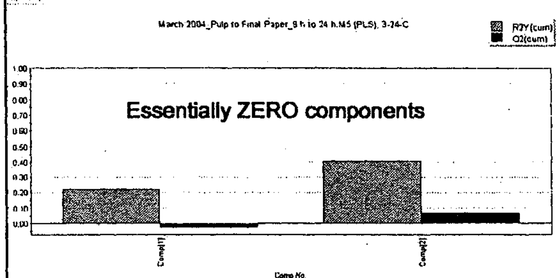
3-24-C

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	$\boxed{\text{3-24-C}}$	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/3-24

ÉCOLE POLYTECHNIQUE MONTRÉAL

3-24-C



3-24-D

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	$\boxed{\text{3-24-D}}$	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use only blocks where basis weight – 45 g/m^2

DEFINITIVE RUNS/3-24

ÉCOLE POLYTECHNIQUE MONTRÉAL

3-24-D

- Zero components

DEFINITIVE RUNS/3-24

ÉCOLE POLYTECHNIQUE MONTRÉAL

3-24-E

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	$\boxed{\text{3-24-E}}$	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/3-24

ÉCOLE POLYTECHNIQUE MONTRÉAL

3-24-E

- No data for this period

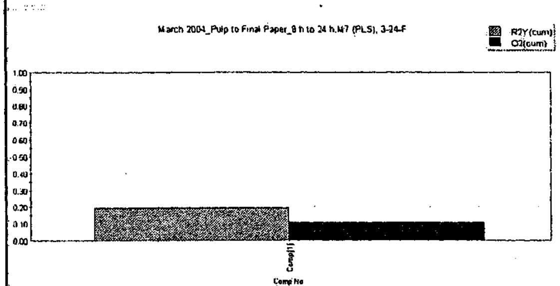
DEFINITIVE RUNS/3-24

3-24-F

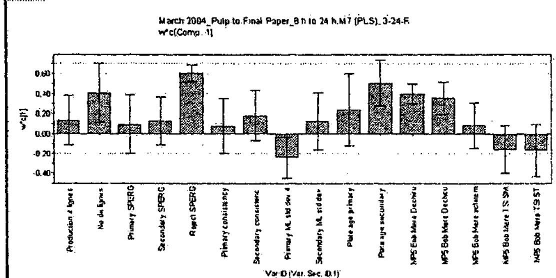
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	$\boxed{3\text{-}24\text{-}F}$	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/3-24

3-24-F



3-24-F



3-24-G

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	$\boxed{3\text{-}24\text{-}G}$	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Use only blocks where basis weight – 45 g/m^2

DEFINITIVE RUNS/3-24

3-24-G

- Zero components

DEFINITIVE RUNS/3-24

3-24-H

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	[illegible]
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	$\boxed{\text{3-24-H}}$
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/3-24

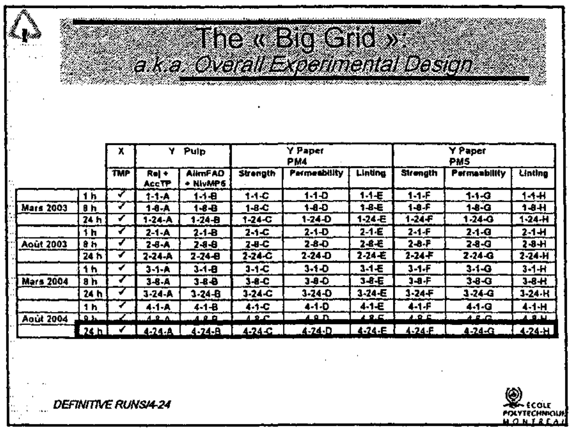
ÉCOLE POLYTECHNIQUE MONTRÉAL

3-24-H

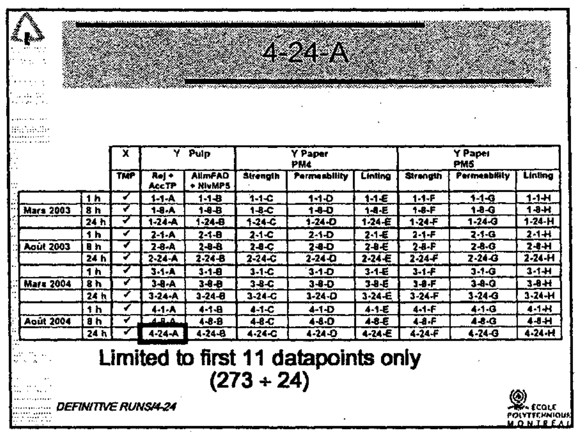
- No data for this period

DEFINITIVE RUNS/3-24

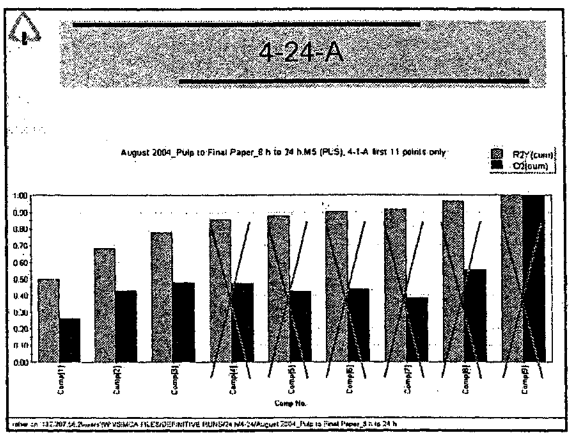
ÉCOLE POLYTECHNIQUE MONTRÉAL

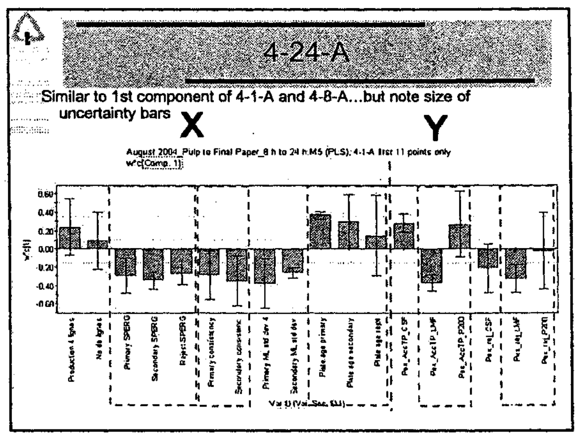


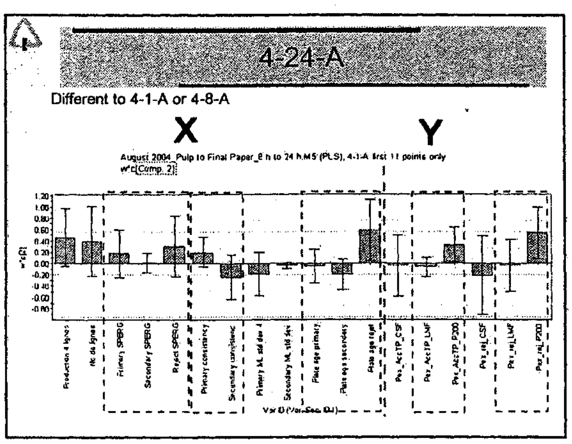
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP6	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

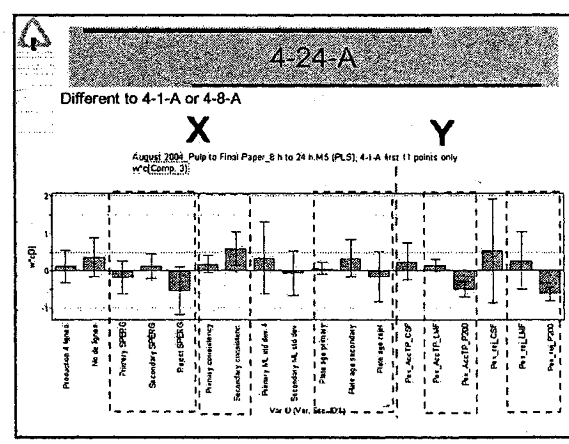


		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H









4-24-B

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP6	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	$\boxed{\text{4-24-B}}$	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

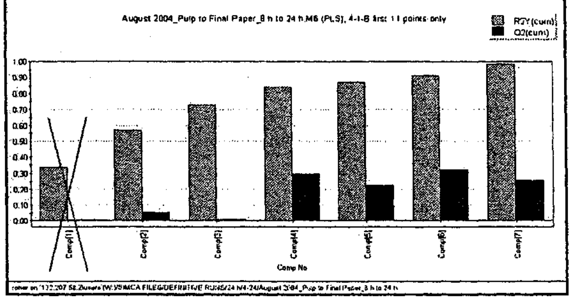
Limited to first 11 datapoints only
(273 ÷ 24)

DEFINITIVE RUNS/4-24

ECOLE POLYTECHNIQUE MONTREAL

4-24-B

Essentially ZERO components



4-24-C

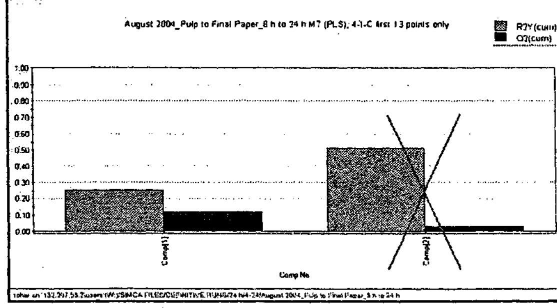
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	$\boxed{\text{4-24-C}}$	4-24-D	4-24-E	4-24-F	4-24-G	4-24-H

Limited to first 13 datapoints only
(318 ÷ 24)

DEFINITIVE RUNS/4-24

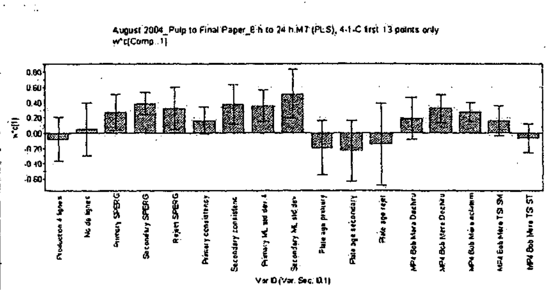
ECOLE POLYTECHNIQUE MONTREAL

4-24-C



4-24-C

Similar to 1st component of 4-1-C



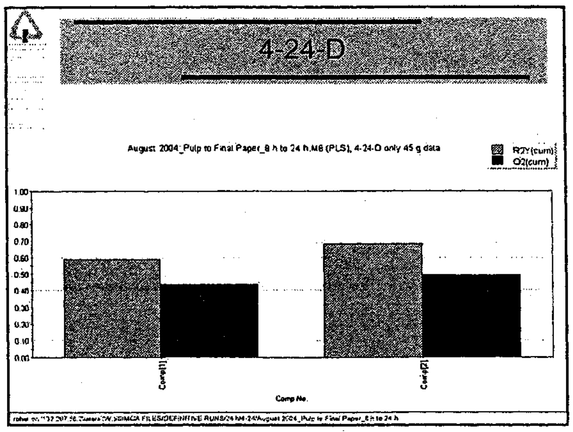
4-24-D

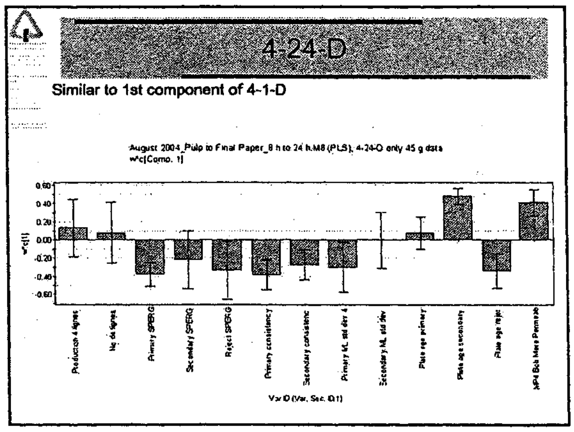
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	$\boxed{\text{4-24-D}}$	4-24-E	4-24-F	4-24-G	4-24-H

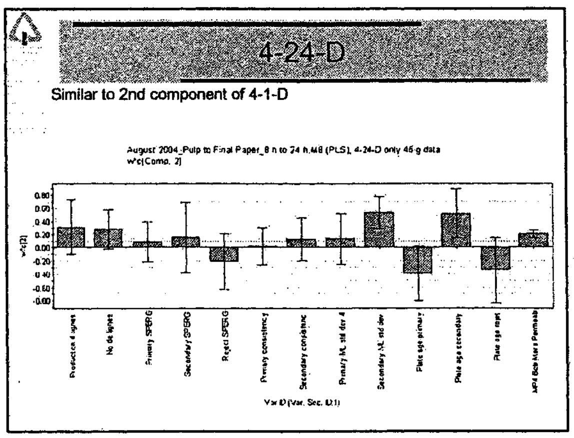
Only use permeability data for periods when Basis Weight = 45 g/m^2 (rest deleted)

DEFINITIVE RUNS/4-24

ECOLE POLYTECHNIQUE MONTREAL





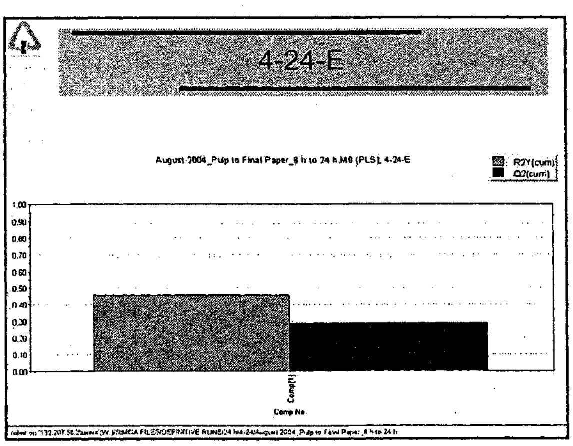


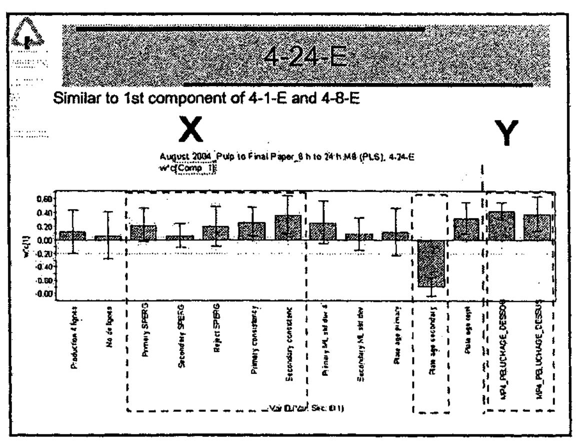
4-24-E

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	$\boxed{4\text{-}24\text{-}E}$	4-24-F	4-24-G	4-24-H

DEFINITIVE RUNS/4-24

ÉCOLE POLYTECHNIQUE MONTRÉAL





4-24-F

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	[illegible]	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	$\boxed{\text{4-24-F}}$	4-24-G	4-24-H

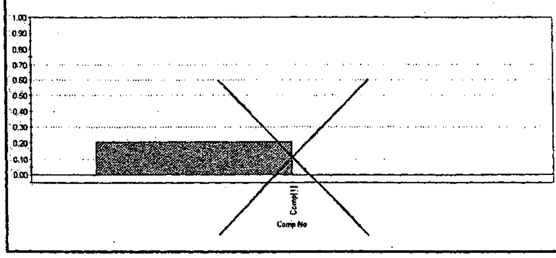
Limited to first 13 datapoints only (318 ÷ 24)

DEFINITIVE RUNS/4-24

ÉCOLE POLYTECHNIQUE MONTRÉAL

4-24-F

Essentially ZERO components



4-24-G

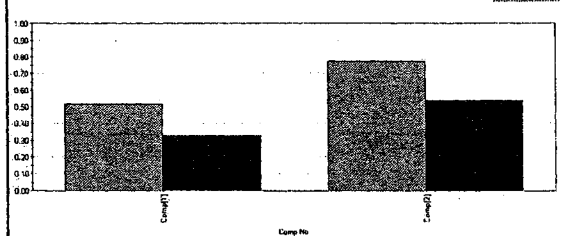
		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMP5	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	[illegible]	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	$\boxed{\text{4-24-G}}$	4-24-H

Only use permeability data for periods when Basis Weight = 45 g/m^2 (rest deleted)

DEFINITIVE RUNS/4-24

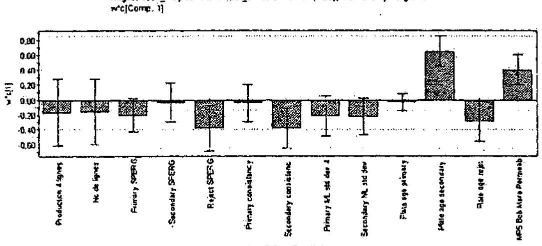
ÉCOLE POLYTECHNIQUE MONTRÉAL

4-24-G



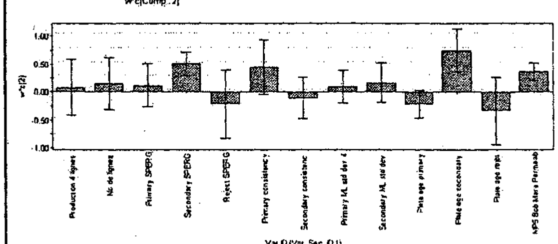
4-24-G

Similar to 4-1-G and 4-8-G



4-24-G

Similar to 4-1-G and 4-8-G



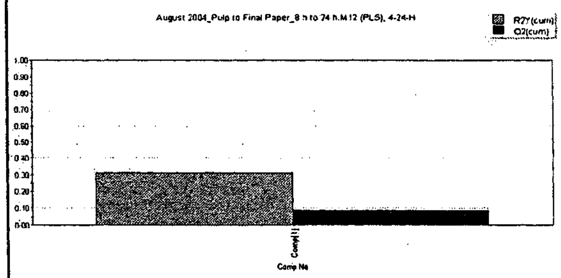
4-24-H

		X	Y Pulp		Y Paper PM4			Y Paper PM5		
		TMP	Rej + AccTP	AlimFAD + NivMPS	Strength	Permeability	Linting	Strength	Permeability	Linting
	1 h	✓	1-1-A	1-1-B	1-1-C	1-1-D	1-1-E	1-1-F	1-1-G	1-1-H
Mars 2003	8 h	✓	1-8-A	1-8-B	1-8-C	1-8-D	1-8-E	1-8-F	1-8-G	1-8-H
	24 h	✓	1-24-A	1-24-B	1-24-C	1-24-D	1-24-E	1-24-F	1-24-G	1-24-H
	1 h	✓	2-1-A	2-1-B	2-1-C	2-1-D	2-1-E	2-1-F	2-1-G	2-1-H
Août 2003	8 h	✓	2-8-A	2-8-B	2-8-C	2-8-D	2-8-E	2-8-F	2-8-G	2-8-H
	24 h	✓	2-24-A	2-24-B	2-24-C	2-24-D	2-24-E	2-24-F	2-24-G	2-24-H
	1 h	✓	3-1-A	3-1-B	3-1-C	3-1-D	3-1-E	3-1-F	3-1-G	3-1-H
Mars 2004	8 h	✓	3-8-A	3-8-B	3-8-C	3-8-D	3-8-E	3-8-F	3-8-G	3-8-H
	24 h	✓	3-24-A	3-24-B	3-24-C	3-24-D	3-24-E	3-24-F	3-24-G	3-24-H
	1 h	✓	4-1-A	4-1-B	4-1-C	4-1-D	4-1-E	4-1-F	4-1-G	4-1-H
Août 2004	8 h	✓	4-8-A	4-8-B	4-8-C	4-8-D	4-8-E	4-8-F	4-8-G	4-8-H
	24 h	✓	4-24-A	4-24-B	4-24-C	4-24-D	4-24-E	4-24-F	4-24-G	$\boxed{\text{4-24-H}}$

DEFINITIVE RUNS/4-24

ÉCOLE POLYTECHNIQUE MONTRÉAL

4-24-H



4-24-H

Similar to 4-1-H and 4-8-H